An application of climate change ensemble averaging methods to fisheries management

Candysse Amy Louise Vrancken

A dissertation submitted in fulfilment of the requirements
for the degree of Master of Science

in the

Department of Mathematics and Applied Mathematics
University of Cape Town

August 2018

Supervisor: Prof Doug S. Butterworth

Administrative supervisor: Prof Hans-Peter Kunzi

Declaration of Authorship

I know the meaning of plagiarism and declare that all of the work in this dissertation, save for that which is properly acknowledged, is my own. I declare that this dissertation has not been submitted to this or any other university for a degree, either in the same or different form.

Signed by candidate

Acknowledgements

This dissertation could not have been accomplished without the assistance and support of a number of people.

Foremost, I would like to express my gratitude to my supervisor, Prof Doug Butterworth, for his patience, willingness to teach and expert guidance over the last two years. Furthermore, I would like to thank the MARAMers for their support and for so willingly proofreading my chapters. In particular, a huge thank you to Andrea Ross-Gillespie for always being willing to answer my many questions and to Rebeccca Rademeyer for generously providing and assisting me with her code. I also wish to thank Di Loureiro for her ever-willingness to help.

I would like to acknowledge my administrative supervisor, Prof Hans-Peter Kunzi, and Dr Chris Jack of the Climate System Analysis Group at UCT for sharing his climate change expertise and for leading me to relevant literature, and the panellists of the 2017 NRF-DAFF International Stock Assessment workshop organised by MARAM for their advice and suggestions.

I am also very grateful to my friends and particularly my home group for their continual prayer and support. There are no words to express my thanks to my family for their unconditional love, encouragement, prayers and so many other things that would take too long to mention. Most importantly, thank you to my heavenly Father whose grace is sufficient for me.

Financial support from the NRF is appreciatively acknowledged, along with the use of the facilities provided by the University of Cape Town's ICTS High Performance Computing team (http://hpc.uct.ac.za).

Abstract

Fisheries management has a long history, having started gradually in the middle of the 19th century. As the awareness of the importance of managing fisheries increased, the need for fisheries scientists and for methodical research into the dynamics of fish populations arose. The methods and science used to manage fisheries have continued to grow and improve since then. Discussions related to climate change have also been ongoing for a long time, resulting in the field of climate change science which focuses on the various components of the natural environment. Both fisheries management and climate change science have similar main objectives, and overall methods for achieving those objectives.

Those similarities are explored using the example of the South African hake fishery (South Africa's most valuable fishery) where, as in other fisheries, problems can occur when an equally weighted average over different assessment models (also termed Operating Models, or OMs) in an ensemble is used. In order to address these problems, a number of methods used in climate change to address similar problems are applied in the case of the hake fishery. The aim is to determine the impact that the application of the model ensemble approaches used in climate change would have had on the recent results obtained from the use of an equally weighted model ensemble average in developing and selecting a management procedure for the South African hake resource. The particular intent of these methods is to reduce any "bias" arising from the use of many models that are rather similar when computing such averages.

Chapter 1 contains a brief introduction to the work. Chapter 2 provides a review of a sample of model ensemble types that are used in fisheries management and/or climate change science. Chapter 3 contains a brief history of the management of the South African hake fishery, as well as a detailed description of the components that make up the management procedure used to manage the resource (OMP-2014). The remaining chapters of the dissertation present the data and methods (Chapter 4), results and discussion (Chapter 5) and the conclusions, along with an outline of possible future work (Chapter 6).

It seems that weighting the OMs in the Reference Set (RS) ensemble for the South African hake fishery using the climate change model weighting methods, among others, and taking model (dis-)similarity and the goodness of fit of the models to the data into account, would not have had a major impact on the results obtained from using the equally weighted model RS adapted in the development and selection of the OMP-2014 for the resource. Since the time taken for a resource below MSYL to recover to MSYL is a key consideration in the very important Marine Stewardship Council certification process, the impact of different weighting schemes for the RS is of interest in this context. All except one (which is not a recommended method) of the unequally weighted approaches result in projections of the spawning biomass of the more depleted deep-water hake species (*M. paradoxus*) reaching MSYL at the same time, or a year later, than the equally weighted OMP-2014 projection. The differences arising from the different weighting approaches are therefore not substantial for the South African hake fishery.

Hence, although these climate change weighting methods can be applied in this fisheries management context, the weights they produced did not add considerable value to the equally weighted average method used currently for South African hake. However, the object here was only to illustrate these approaches. It could well be that for other fisheries, the weighting scheme could have a greater effect on the eventual results and decisions. The weighting of individual models in an ensemble continues to be of increasing interest in many different fields, including fisheries management and climate change. A continued investigation into other weighting methods that may impact the selection of OMPs for the South African hake and other fisheries is certainly warranted.

Contents

Chapter 1

Introduction

Some fisheries resources had already started declining by the middle of the 19th century. To address that issue, one of the initiatives taken in the US was the creation of the U.S. Commission on Fish and Fisheries by Congress in 1871. In Europe, the Christiania Conference in 1901 endorsed scientific inquiry as the basis for a rational exploitation of the sea, and several countries attended the inaugural meeting of the International Council for the Exploration of the Sea (ICES) in 1902[1] (Went 1972). Overall, the period from 1885 to about 1950 was one of slowly increasing fisheries research, but without the research findings having a substantial effect on fisheries management (Smith 1966). Historians argue that the factor which triggered the full development of American fisheries management occurred towards the end of that period. That factor was Japan's increasing interest in fishing for sockeye salmon in Alaska during the 1930s (Oreskes and Finley 2008).

Fisheries science as a recognised field of research began in the 1950s, building on work already conducted between the two world wars (NOAA 1993). Around the same time, at the governance level, a number of conventions were adopted such as the Whaling Convention of 1946 and the Northwest Atlantic Fisheries Convention of 1953. After the Conference of the Food and Agricultural Organisation (FAO) of the United Nations authorised the creation of regional fishery bodies in 1959 (Koers 1973), fishery science became widely accepted and a number of Regional Fisheries Management Organisations (RFMOs) were created worldwide (Tetzlaff 2015), many of them under the auspices of the FAO.

It was during that period that foreign fishing activities along the South African coast increased dramatically and resulted in the South African government taking action by proclaiming an Exclusive Fishing Zone (EFZ) in 1977. A few years earlier, the government had reacted against this increased foreign fishing threat to the economic viability of the local industry by appointing the 1971 Du Plessis Commission (Du Plessis *et al.* 1971). The latter was later followed in 1986 by the Diemont Commission, which was tasked with inquiring into, and making recommendations on, the allocation of quotas for the exploitation of living marine resources (Diemont *et al.* 1986).

During the last twenty years, widespread dissatisfaction with argued inadequate success of RFMOs in promoting adequate resource conservation has led to a call for strengthening them (OECD 2009). The United Nations General Assembly and several regional international organisations or arrangements have also turned their attention to the management of deep-sea fisheries (Oanta 2018). It must be stressed, however, that the debate is much wider than the issue of effectiveness of specialised institutions or arrangements. Indeed, it is now widely

[1] ICES was established in 1902 as a result of conferences held in Stockholm in 1899 and in Christiania in 1901.

accepted that one needs to focus not only on the natural ecosystems, but also on the socioeconomic systems as well as the relationships between them (Hauck and Sowman 2003).

Irrespective of the complexity of the factors taken into account, the main aim of fisheries management is always to make management decisions that will ultimately result in the most desirable outcome. Before a decision can be taken, for each possible action, the possible outcomes and their associated probabilities must be assessed (Hilborn and Walters 1992). This is traditionally the realm of stock assessment and modelling, with fisheries scientists spending the majority of their time on such evaluation activities. A summary of the main mathematical techniques used in fisheries management can be found in the appendix to this chapter (Appendix 1.A).

Debates around climate change are at least as old as debates around fisheries management (Fleming 2005). The phenomenon has generated a wide range of views over the past century (Howe 2017), as well as the creation in 1988 of the UN Intergovernmental Panel on Climate Change (IPCC) (Bolin 2008) and the adoption in 1992 of the UN Framework Convention on Climate Change, very recently strengthened by the Paris Agreement in 2015.

Those developments have given rise to the new discipline of climate change science. The discipline focuses on the various components of the natural environment including the world oceans and involves the development of mathematical climate models, which enable projections of future climate scenarios (Farmer and Cook 2013).

Although their objectives are different, the aims of fisheries management and climate change science are similar, as are their overall methods, i.e. modelling and scenario projection. It is therefore not surprising that similarities exist between the use of model ensembles (combinations of multiple individual models) in the two fields. More specifically, the problem of how to weight results from different models in the ensembles to get a "best" representation across their differing results, is common to both fields. It is generally not possible to develop a model which describes the relevant complex system completely accurately, and this leads to uncertainties regarding the final model choice. In order to take this uncertainty into account, both fields develop multiple models to describe the complex systems, and attempt to find a summary over the results in order to determine a more reliable overall projection.

There are many cases where model ensembles are used in fisheries. However, in this dissertation, the South African hake fishery, which harvests two morphologically similar species, the shallow-water Cape hake (*M. capensis*) and the deep-water Cape hake (*M. paradoxus*), is used as an example because it is the most valuable in South Africa. It is managed using an Operational Management Procedure (OMP) whose development involves the use of an ensemble of models. The 2014 OMP choice was based on the overall projection being set equal to the average over the eleven models in an ensemble (called the "Reference Set" (RS)), with each model's projection being equally weighted. Problems may occur, however, when this equally weighted model average is used. Results can easily become biased in some way if there are many rather similar models in the ensemble.

In order to address this problem, this dissertation investigates whether one or more methods used in climate change to address similar problems can be applied in the case of the hake fishery. For this study, the aim is to determine the impact that the use of the model ensemble weighting approaches used in climate change would have on the current results obtained from the treatment (equal weighting) of a model ensemble in developing an OMP for the South African hake resource.

Dissertation outline

Chapter 2 provides a review of a number of model ensemble types that are used in fisheries management and/or climate change science. It does so by focusing first on fisheries ensembles. After identifying uncertainties related, among others, to model structure, examples of ensembles in fisheries literature, including how they

are weighted, are listed before the management practices of specific fisheries are illustrated. The review then turns to climate change ensembles by identifying uncertainties and giving examples of ensembles in the climate change literature with their associated weighting methods. Finally, the uncertainties and examples of ensembles in fisheries management are compared to those in climate change.

Chapter 3 contains a brief history of the management of the South African hake fishery, with a detailed description of the components that make up the OMP used to manage the resource (OMP-2014). As far as this OMP is concerned, the collection of hake assessment data is described, the assessment method, Operating Models (OMs) and OMPs[2] considered are presented with additional details in two appendices, and the OMP specifications and projections of various model outputs are provided.

Chapter 4 focuses on data and methods. The data and model estimates that are used to compare and find weights for the individual models in the ensemble are detailed. The model estimates are the time series of spawning biomass and numbers-at-age, and the data are the available CPUE time series. The method of multidimensional scaling (MDS), which allows the visual representation of the (dis-)similarities between models, is described in an appendix (Appendix 4.B), along with the different model weighting methods used (Appendix 4.C).

Chapter 5 presents and discusses the results of the main analyses and methods described in Chapter 4 when applied to hake. More specifically, it provides and evaluates the results of the MDS analyses, the different weights for each of the models in the ensemble (obtained using the weighting methods) as well as projections under OMP-2014 using the weighted ensemble. Finally, Chapter 6 provides a brief summary of the main findings and conclusions of the dissertation before outlining some possible future work.

The software used for the modelling work is AD Model Builder, a powerful statistical package for estimating parameters for nonlinear models (Fournier *et al.* 2012), and model runs were performed using facilities provided by the University of Cape Town's ICTS High Performance Computing team (http://hpc.uct.ac.za). The software used to perform MDS was SPSS (IBM Corp. 2016). All graphical output was generated in R (R Core Team 2015) and Matlab (MATLAB 2016).

Specification of naming and terminology conventions used in this dissertation

For the description of biomass units, "tonnes" (i.e. a metric ton of 1000 kg) will be used. The biomass at which the maximum sustainable yield (MSY) is achieved may be referred to either as B_{MSY} (when an absolute tonnage) or MSY level (MSYL) (when a relative measure B_{MSY}/K). MSYL will be used throughout this dissertation for consistency.

A summary of some approaches to fisheries management and the associated terms used in this dissertation is included in Appendix 1.A.

Throughout this dissertation, the term "sensitivity" has been used to refer to the sensitivity of the result(s) from a stock assessment to changes in the specifications of that assessment. "Robustness", on the other hand, is used when referring to the extent of changes in the performance statistics of a Management Procedure (MP) to modifications to the OM against which it is tested. The MP is more robust if these changes are smaller.

[2]Explanations of the meanings of these technical terms are provided in an appendix to this chapter (Appendix 1.A).

Appendices

1.A Some Approaches to Fisheries Management

There are two main approaches for providing scientific recommendations (e.g. Total Allowable Catches (TACs)) for management measures for fishing renewable marine resources: the "traditional assessment" (TA) approach and the Management Procedure (MP) approach (Butterworth 2007).

The TA involves the development of a "best assessment" of the resource, i.e. a mathematical model that incorporates all (or at least most) of the available data for and knowledge about the resource, and is considered to provide a better representation of the fishery together with the resource and its dynamics than any other possible alternative model. This approach can also be based on an ensemble of models in which case the "best assessment" may be chosen as the median of the ensemble. This "best assessment" provides estimates of resource abundance and productivity, which are used to determine scientific recommendations by, for example, applying a harvest control rule (a set of well-defined management actions that will be taken in response to the status of a stock and changes in this status). Often, this process is repeated annually. Butterworth (2007) suggests that the TA has a number of disadvantages, one of which is that the best assessments can vary substantially from year to year; this can lead to appreciable but unnecessary variation in TAC recommendations over time, which is not ideal for industry. Another disadvantage is that the TA is unable to properly consider longer-term trade-offs between risk to the resource and long-term catches. Furthermore, the TA approach does not formally allow for the consideration of uncertainties regarding the best assessment, i.e. by how much it might be wrong.

The MP approach provides scientific recommendations using a formula, where the inputs to this formula (such as abundance indices from surveys) have been prespecified. An important distinction between the MP and TA is that the MP formula is tested using simulations to make sure that it can reliably provide desired trade-offs (amongst, e.g., maximising catch, minimising risk of unintended depletion of the population and minimising interannual catch variation). The MP must also be able to achieve the trade-offs even if the best assessment of the resource is in error. In order to adjust for such errors (uncertainty), it relies on a feedback control mechanism. Thus a number of plausible alternative scenarios Operating Models (OMs) describing the fishery and resource dynamics are developed, usually based on stock assessments, and used as the basis for the simulation tests from which the anticipated performances for different MPs in terms of measures such as catch and risk are determined.

OMs are mathematical models that describe the broad behaviour of a system and should include biological dynamics, how these relate to available data, process and observation error, age structure, etc. The OM has parameters for some of which the values are unknown. In order to estimate these parameters, the model is fitted to the available data using one of a number of procedures, for example, maximum-likelihood or Bayesian estimation (Hilborn and Walters 1992). The "best assessment" model referred to above is usually one of the OMs.

Often a group of OMs called a Reference Set (RS) is chosen so as to include the primary sources of uncertainty in the assessment. These OMs are usually variations of the Reference Case (RC), for example each OM in the RS could have a different stock-recruitment relationship, if there is uncertainty about which stock-recruitment relationship best represents reality. The MP approach uses this RS in order to cover the main range of alternative plausible scenarios for the underlying dynamics of the resource, and thus captures the most important aspects of this uncertainty. The OMs are then projected into the future under different MPs. Key performance statistics (e.g. biomass level relative to maximum sustainable yield level (MSYL)) are chosen to summarise the results of different trials and to allow considerations of trade-offs to be discussed by stakeholders.

The MP approach is claimed to have a number of advantages (Butterworth 2007). The time that is often spent deciding on the best assessment each year in the TA can be used instead for research towards resolving the uncertainties regarding aspects of the population and the models, and the simulation testing framework allows for a formal and detailed evaluation of risk. The MP approach also provides a basis for putting limits on interannnual TAC variability, unlike the TA, as well as a framework for different stakeholders to interact and discuss management objectives.

Some disadvantages to the MP approach include a lengthy development time, although once the MP is in place, discussion time usually decreases substantially. Complications that arise from poor availability of input data are another complication; it is, however, possible to make provisions for this (Butterworth 2007). There is also the disadvantage of still having to choose a RC OM, with the primary results for MP performance often heavily dependent on this choice. Unlike with the TA, the MP approach has the advantage of having tested for the adequacy of feedback to correct for any error (Butterworth 2007). As mentioned, once the MP is in place, the intent is that it be used for a number of years. This is an advantage but can also be a disadvantage if appreciable changes occur concerning perceptions of the resource in the meantime, for example if new data are forthcoming that contradict previous assumptions made while developing the MP.

Provisions are often made describing how to handle this situation if it arises, which often involve a review of the MP, whether as one in a regular review schedule or not. These are often called "Exceptional Circumstances" provisions and are a formal list of "metarules" which pre-specify what should happen in the case of exceptional circumstances when using the TAC generated by the MP is considered to be highly risky or inappropriate (Rademeyer *et al.* 2010). In South Africa, MPs are called Operational Management Procedures (OMPs), emphasising that they constitute the rules applied in practice as distinct from a more theoretical concept.

Overall, the MP approach solves most of the problems that occur in the TA, with the main advantages being a basis for limiting of interannual TAC variation and the formal accounting for scientific uncertainty using simulation testing.

Chapter 2

Model ensembles

2.1 Introduction

When it comes to modelling complex processes, whether they are fisheries or climate systems, there are always several uncertainties; this chapter describes the main types of these uncertainties. The magnitudes of these uncertainties vary and model ensembles are constructed in an attempt to reflect this. The different types of model ensembles used in fisheries and climate sciences are discussed here, with examples from the literature. The way in which some specific fisheries analyses address uncertainty is also discussed. Finally, an overall comparison is made between uncertainties and the use of ensembles in fisheries management and in climate change science.

2.2 Fisheries ensembles

2.2.1 Uncertainties

There are four main types of error or uncertainty in fisheries management. The first type is observation error, that is to say the error that occurs because the data that are collected from both the commercial sector and from surveys involve sampling variability. Moreover, measurements associated with some of the input data involve error, for example, the ring count estimates taken from otoliths to estimate age (Haddon 2001). These data are used to estimate model parameter values which leads to uncertainties concerning these values. There are also parameters for which the values are unknown or cannot be estimated independently, in which case those parameters are often given fixed values about which there is uncertainty (e.g., natural mortality is often accorded a value assumed to be constant in population models) (Haddon 2001). Process error is another type of uncertainty. It accounts for the inability of simple models to describe complex biological processes exactly. It arises when a model has been defined deterministically but some of the components vary (possibly randomly) through time (Haddon 2001). Model structure error arises because there is no way of knowing if the model chosen to represent the complex ecological behaviour is the best representation of the system. This error incorporates several types of uncertainties, such as uncertainty regarding the accuracy of the assumptions made in the modelling process. Lastly, implementation error occurs because, although it is assumed that future

catches equal the TACs set exactly, in practice this is usually not the case. This can be for reasons such as poaching and unexpected changes in the behaviour of fishers.

2.2.2 Examples of ensembles in fisheries literature

There are two main types of ensembles used in fisheries management: superensembles and multi-model ensembles (MMEs).

Superensemble modelling involves the input of predictions from a group of models into a separate statistical model: the superensemble (Krishnamurti *et al.* 1999). The superensemble is fit to a training dataset for which outcomes are well known and is then used to make predictions. Superensembles have a number of advantages, two of which are that: 1) they can be tailored to predict specific response variables, and 2) they allow model predictions to be combined using non-linear functions, which allows the useful parts of each of the candidate models to be pieced together to build a model with improved performance (Anderson *et al.* 2017). The aim of the methods in this dissertation is, however, to develop procedures (and particularly MPs) for recommending TACs which show robustness across different models by using weights which prevent models that are too similar from causing bias in the results. For this reason, superensembles will not be discussed further here.

MMEs are, as the name suggests, ensembles that consist of multiple models. In fisheries, when developing MPs, the ensemble is often a RS consisting of multiple OMs. MMEs are extremely useful and a better reflection of reality because they allow for the incorporation of several uncertainties and assumptions instead of having to choose one "best" model. A further advantage is that these ensembles and the results they produce can be used and analysed in different ways, taking into account either the individual responses of the models or the overall response of the ensemble.

There are many examples of cases in fisheries in which the individual responses of different models are considered. A few are highlighted here, commencing with Gardmark *et al.* (2013). The Eastern Baltic cod is used as an example of a proposed "biological ensemble modelling approach". The main aim of the paper is to consider several different models in an ensemble with different ecological assumptions for climate forcing, using multiple realisations for each climate scenario. The approach consists of three steps. The first is to determine an ecological mechanism that explains the differences in the responses amongst models. This is done by separating the ensemble into subsets based on key ecological assumptions and then comparing the simulated projections. The second step involves separating model assumption uncertainty from statistical uncertainty as regards future climate by comparing results among models within one climate realisation, and within models among multiple climate realisations. The third and final step involves identifying results that are common over the entire ensemble. In order to obtain these common (and hence model-independent) results, alternative management scenarios were evaluated through within-model comparisons of how they performed in relation to specific targets. An option (or decision) table was then compiled based on these comparisons of simulated future Eastern Baltic cod responses to alternative climate and fishing scenarios. Using this table, it was possible to determine the effect that different model responses had on management advice, and to find results which were valid across the entire ensemble, despite the differences in the models. This option table hence demonstrated where there was robustness in the presence of uncertainty. It showed comparisons within models of simulated responses in relation to specified target levels that allow robustness to be checked across all of the models. Robustness is thus evaluated from the individual responses of the models.

When considering, instead, the mean response from the ensemble, the most popular ways of integrating across the model results are Bayesian methods or weighted averages. With Bayesian model averaging (BMA), prior probabilities are specified on the basis that each of the models is the true model and for each model, a joint prior is specified over the parameters (Hoeting *et al.* 1998). Then the posterior distribution comprises a weighted average of the models, where the weights are Bayesian posterior probabilities that the given model is the true model, conditional on the data (Hoeting *et al.* 1998). Simple weighted averaging often involves taking the average over the OM results with each OM having a weight, sometimes determined by the closeness of the fit of the model to the data (e.g. Akaike Information Criteria (AIC) (Akaike 1973) weighting), but often determined simply by appeal to expert opinion. This simple averaging is the method on which this dissertation will focus.

This method is used, for instance, in Scott *et al.* (2016)'s work. The authors use the Iberian hake stock to demonstrate a framework that allows multiple sources of uncertainty to be integrated into the stock assessment process. A suite of stock assessment models, containing different assumptions about the stock and the fishery, is developed and conditioned (fitted to) the data available. The framework also entails the estimation of parameter values and the integration across the results to determine a multi-model outcome. A model weighted averaging method is used for this integration. The averaging method is based on the generalised cross-validation (GCV) score, which is estimated by means of an analytical expression and is a measure of the predictive accuracy of the model; this can be used, along with data, to determine the quality of the fit. In the study, the GCV scores of the catch-at-age matrix were calculated and each model variant was given a weight based on the median score across its iterations, which was used as a measure of how well each model fitted the data.

Other, more simple, methods of model selection or averaging which are based on how well the models fit the data include the AIC or the Bayesian Information Criterion (BIC) (Schwarz 1978). In this context, the goal is to determine which model has the best predictive accuracy in that it is expected to fit future observations well. AIC and BIC are the two most popular determinants of appropriate model parsimony (better fit but too complex a model for reliable parameter value estimation), with equations (Aho *et al.* 2014) as follows:

$$AIC = -2ln(L(\hat{\theta})) + 2p \tag{2.2.1}$$

$$BIC = -2ln(L(\hat{\theta})) + pln(n) \tag{2.2.2}$$

where $L(\hat{\theta})$ is the likelihood of the estimated model, p is the total number of parameters where values are estimated when fitting the model to data and n is the sample size. For both indices, smaller values indicate more preferred models.

There continue to be discussions on whether to choose AIC or BIC as a model selection metric. An example is the International Whaling Commission (IWC) Working Group on Ecosystem Modelling's debate on whether to use AIC or BIC in the analysis of the decline in energy storage in Antarctic minke whales during the period of Japan's research program in the Antarctic (JARPA)[3]. In Annex K1 of the Working Group's report (International Whaling Commission 2015), opposing opinions are evident. McKinlay and de la Mare (2015) argue that the choice of which information criterion to use depends on the purpose of the analysis, the sample size and the details of the experimental design. They note that choosing BIC over AIC is reasonable only if the sample sizes are very large in the context of the model. On the other hand, Konishi and Walloe argued

[3]JARPA started in 1987 in response to claims of uncertain scientific information on whale stocks and was conducted for 18 years.

that BIC should be chosen to select the best model in this particular complex situation where there are many variables, random effects and interaction terms as well as a large number of data points (International Whaling Commission 2015). Zeh agreed that the goals for the modelling exercise must be clear when choosing a model selection metric, but considered that the models chosen using the more conservative BIC would provide more robust parameter estimates compared to those chosen using AIC (International Whaling Commission 2015).

Cunen *et al.* (2017) discuss the use of another selection metric called the Focused Information Criterion (FIC) in the study of Antarctic minke whales, which is used when the aim is to find the "best model", that is to say the one which gives the most precise estimates of the parameter of primary interest (Claeskens *et al.* 2003). First a wide model is chosen, which is intended to include all the biologically relevant effects and parameters, and the candidate estimation models are often simplified versions of this wide model. In this instance, the main question of interest is whether there was a significant (linear) trend with time or not. Here, a new FIC criterion was developed for linear mixed effect models. The FIC scores for all candidate models are computed with respect to the wide model. Since the goal is to estimate the focus parameter as accurately as possible, a natural step is to choose the candidate model which has the smallest mean squared error (MSE) in the estimation of that parameter, because the true value of the parameter is unknown. The FIC score of each model is an estimate of the MSE associated with the model's estimate of the focus parameter. An issue with the FIC scores is that they depend to some extent on the wide model chosen.

Another example of the use of an ensemble of models is found in Redfern *et al.* (2017), who explore methods of overcoming the limitations that arise in attempting to predict cetacean distributions in data-poor marine ecosystems, using blue whales as a case study. Two different ecosystems were considered, each with its own data set. For each data set, one species distribution model (a generalised additive model (GAM)) was built using a spline for each of the five variables (distance to the shelf edge, wind speed, sea surface temperature, sea surface salinity and sea surface height), and ten further models were built by replacing each pair of variables with an interaction term and using a spline for the three remaining variables. Four measures of model performance were used to assess how well the ecosystem-specific models predicted ecosystem distributions: area under the receiver operating characteristic curve (AUC) (Fawcett 2006), true skill statistic (TSS) (Allouche *et al.* 2006) and the percentage of sightings contained in the highest 2% and 10% of predicted densities. The AUC and TSS are widely used as measures of performance for models that generate presence-absence predictions, which is the case in this example. The AUC is used to compare model predictions within each ecosystem, while the TSS is a threshold-dependent measure of model performance. Each model was then assigned four ranks based on the measures of model performance. In this case, the mean of the four ranks was used to select the best model for each ecosystem. It would, however, be possible to use the mean ranks as weights and take the weighted mean over all the models instead of choosing only one "best" model.

2.2.3 Management of specific fisheries

When it comes to the management of specific fisheries, there are a number of different ways in which uncertainties are considered and investigated. In some cases, such as the South African South Coast rock lobster, the New Zealand rock lobster and the Atlantic halibut resources, a single Reference Case (RC) model is used and uncertainties are taken into account through a few robustness tests. In other cases, ensembles of multiple OMs taking main uncertainties into account (as described in Section 2.2.2) are used along with robustness tests.

For the South African South Coast rock lobster, a single RC OM, considered to be the best assessment of the resource, was used for simulation testing of the current South Coast rock lobster OMP-2014, where the

assessment was based on penalised maximum likelihood estimation (PMLE) (Johnston and Butterworth 2017c). Robustness tests investigated sensitivities to time-varying selectivity, growth rate value, the stock-recruitment relationship and for alternate weights to the catch-at-length data in the log-likelihood (Johnston and Butterworth 2017c).

There are currently eight New Zealand rock lobster stocks with MPs which were adopted largely because of the need to rebuild depleted stocks. The main component of these MPs is a harvest control rule which defines the relationship between the input catch per unit effort (CPUE) data and the output Total Allowable Commercial Catch (TACC) (Breen 2015). The harvest control rule is either a "plateau step" or a "plateau slope" rule (Breen 2015). Each MP uses an OM based on its respective stock assessment model. An example of one of the MPs is that described by Starr and Webber (2016). The stock assessment that provided the OM used for this was a Multi-stock length-based model (MSLM), which was fitted to catch, size frequency, CPUE and tag-recapture data. The assessment was Bayesian and was implemented using the Markov chain Monte Carlo (MCMC) approach. Two equally credible base case runs were selected by the assessment, differing only in the assumption of whether growth did or did not show a density dependent response. The assessment model was used as the basis for an OM to test Management Procedures (MPs). The rules tested were to determine the annual TACC. Each rule was tested with 1000 simulations, based on the MCMC posteriors from both base case runs in order to address parameter uncertainty. Rule behaviour under alternative OM assumptions was tested using a number of robustness trials.

As described by Cox *et al.* (2016), the Atlantic halibut resource is currently managed using a single reference case OM. A statistical catch-at-length assessment model (SCAL) is used for stock assessment, estimating historical biomass, fishing mortality, recruitment and biological reference points. Between stock assessments, an interim procedure is applied to provide annual TAC advice, which uses an empirical harvest control rule based on halibut longline survey data. The operating model (HAL) is used for evaluating the performance of alternative TAC interim procedures. The framework model (SCAL) and the OM (HAL) currently depict similar population and fishing dynamics in the four main fisheries.

In contrast to the cases above based on single OMs, in other cases, ensembles of multiple models taking uncertainties into account, are used along with robustness tests. The current South African hake OMP was selected based on performance across a RS of 11 OMs and the results were averaged with all of the model projections having equal weights. Chapter 3 details the management history of the resource and the current OMP.

Similarly, the South African West Coast rock lobster (WCRL) OMP was selected based on the performance across alternative OMs, but with each OM being given its own weight. Since OMP-2003, two RC assessment models have been used (Johnston and Butterworth 2005). For each OMP (OMP2003, OMP-2007 and OMP-2011), a number of uncertainty factors were considered, with representative scenarios agreed upon for each of those factors. In order to integrate over the OMs, weights were determined for each set of scenarios. These weights took into account each scenario's relative plausibility and were determined by experts in the WCRL scientific working group (SWG). For the most recent OMP (OMP-2011), the weight was obtained for each OM by multiplying together the weights for each of the four main uncertainty factors (median future recruitment x future somatic growth x current abundance levels x future poaching levels) (Johnston and Butterworth 2011), with past and future poaching levels being the largest source of uncertainty (Johnston and Butterworth 2017b). The resource is presently being managed using a number of mechanisms including minimum size limits and gear restrictions but the TACs indicated by the OMP constitute the main control mechanism.[4]

[4] "Exceptional Circumstances" provisions have been invoked recently because of an updated assessment in 2016 and a re-evaluation of poaching levels, which indicated a large increase in poaching in the recent years (Johnston and Butterworth (2017a)).

The Southern Bluefin Tuna (SBT) stock is managed internationally by the Commission for the Conservation of Southern Bluefin Tuna (CCSBT). A wide range of plausible scenarios (constituting a RS) was selected considering uncertainties with regard to historical data, life history and fishery factors/parameters (Hillary *et al.* 2015). The various parameter values and scenarios in the RS were weighted. Table 2.1 details the structure of the RS (Parma *et al.* 2017). Each OM is given weights for each of the factors/parameters with the net weight for the OM being obtained by multiplying those weights together. In addition, an overall average was taken over all the operating models in the RS. The table shows that the three weighting methods used were: "uniform prior" (the selected values for the parameter get equal weights), "ObjFn Sampling" (values are given likelihood weights) and prior distributions imposed on the basis of expert opinion. Robustness trials were also conducted by incorporating more extreme hypotheses about data, model structure and future processes (Hillary *et al.* 2015).

2.3 Climate change ensembles

2.3.1 Uncertainties

Predictions of regional and local changes in climate are subject to considerable uncertainty. This uncertainty comes from three distinct sources. Internal variability of the climate system involves naturally occurring fluctuations (Hawkins and Sutton 2009). Scenario uncertainty involves uncertainty in emission scenarios as well as model projections for the given scenarios (Tebaldi and Knutti 2007). Finally, model or response uncertainty occurs when different models, in response to the same radiative forcing (e.g. changes in atmospheric concentrations of greenhouse gases), simulate different changes in climate (Hawkins and Sutton 2009).

This is over and above the fact that numerical models have, in and of themselves, their own set of uncertainties (Tebaldi and Knutti 2007). One of them is initial condition uncertainty, which involves the assumptions made in choosing the initial conditions. This uncertainty is most pertinent for short time scales, as long-term projections are usually averaged over decades and are thus largely insensitive to small variations in initial conditions. Another is boundary condition uncertainty, which arises because model experiments, which are otherwise self-contained, rely on inputs that represent external influences, such as the solar cycle and greenhouse gas emissions. A further type of model uncertainty is structural uncertainty which is caused by choices made in the design of the model. Finally, model parameter uncertainty has two components: parameterisation uncertainty involves the choices that need to be made on how to parametrise complex climate processes, while parameter value uncertainty considers the decisions made concerning the values for each of the model parameters. The latter uncertainty is often explored using perturbed physics ensembles (PPE), which are sets of simulations using a single model but different choices for various parameters (Tebaldi and Knutti 2007). PPEs will be described in more detail in the next section.

2.3.2 Examples of ensembles in climate change literature

There are two main types of model ensembles used in climate change.

The first type is the PPEs mentioned earlier in which one model is run multiple times with different parameter values (Knutti 2010). Often, the model is a global climate model (GCM) and the ensemble is built in a way that samples the widest possible range of uncertainties with parameter values being chosen by experts (Murphy

et al. 2004). PPEs can also give quantitative estimates of the robustness of the simulated changes (for example, changes in surface air temperature and precipitation) to the modelling uncertainties (Murphy *et al.* 2004). This information assists in reliably separating anticipated regional change from the noise of natural variability, giving planners an improved basis for the development of suitable response strategies (Murphy *et al.* 2004).

An example of analyses conducted with PPEs is found in McSweeney *et al.* (2012), where the approach was to select sub-sets of an ensemble based on model performance. It is important to note that climate projections that go decades or more into the future cannot, by their nature, be validated by comparison with observed changes. Therefore, in order to determine whether a climate model has predictive ability, its capacity to replicate well-understood climate processes and climate conditions for which observation data exist must be investigated (Tebaldi and Knutti 2007). The aim of the McSweeney *et al.* (2012) study was to find a sub-selection from a 17-member PPE of GCMs that would account for the range of uncertainty which the full ensemble implies, while minimising the computing and post-processing resources required. The goal was to provide a range of outcomes within which future climate change may lie. First, the performance of ensemble members in simulating the climate of the region was assessed to see if any should be eliminated because they did not represent the key climate processes of the region. Secondly, the range of future projections was explored and a subset selected that captured a wide range of responses. The responses in the PPE ensemble and in the chosen subset were then compared with the responses in the widely known multimodel CMIP3 (Coupled Model Intercomparison Project, phase 3) ensemble (Meehl *et al.* 2007).

The fact that there are many different ways to design a parameterisation means that PPEs are unable to capture the full range of uncertainties (Tebaldi and Knutti 2007). Structural uncertainties also need to be considered to make sure that the results from a single model are not a direct result of the model structure (Tebaldi and Knutti 2007). This is the main reason for considering an ensemble consisting of multiple models instead of just one model. The CMIP MME was developed to allow the assessment and comparison of many different models as well as to determine why and by how much their results differed (Taylor *et al.* 2012), with the most recent being CMIP, phase 6 (Eyring *et al.* 2016).

There are many ways of aggregating the ensemble results, each with its own advantages and disadvantages.

The probabilistic approach applies probability distributions to uncertain climate change parameter values. New *et al.* (2007) explore the implications, using a large PPE, of a probabilistic risk-based framework for climate impact assessments using water resources in the Thames River as an example. They show that the probabilistic approach provides more informative results, enabling the potential risk of impacts to be quantified. Probability distributions are, however, impossible to specify exactly due to a lack of data and to multiple uncertainties. This means that the output probability of certain events is highly dependent on the probability density functions (pdfs) used to represent the uncertainties in the values of the model parameters. These pdfs are determined by experts using available data and resources. This becomes problematic when experts have differing opinions. Webster *et al.* (2002) also used this approach to develop a consistent set of emission scenarios with known probabilities based on a model of the world economy. They performed a sensitivity analysis to identify the most important parameters. The pdfs for these parameters were constructed by appeal to expert opinion and by consulting the literature. Pdfs for greenhouse gas emissions were produced by use of a Monte Carlo simulation for each time period.

When working with MMEs, there are a number of concerns, one of which is that the sample of models in the ensemble might be neither random nor systematic. This means that the ensemble could either underestimate and/or misrepresent the uncertainty as well as the variance in the climate system (Knutti 2010). Averaging

over or combining the results from multiple models can be biased to some extent if there are many rather similar models in the ensemble. Model similarity and dependence occur frequently in large climate ensembles where code and variation data are shared (Tebaldi and Knutti 2007)). For this reason, methods to find an "unbiased" (more reliable/representative) average are being explored generally, and are a particular focus of this dissertation.

As described in Section 2.2.2 of this chapter, two of these averaging approaches are Bayesian methods and weighted averages. They have been found to perform better than simple averages where each model is weighted equally (Tebaldi and Knutti 2007). Using the methods, models in MMEs are weighted according to some measure of model performance. Because no single model is best with respect to all variables, attempts must be made to use multiple diagnostics and metrics of performance to determine model weights that account for correlations within the ensemble, as well as uncertainty in observations and in the model's ability to represent climate processes of interest (Tebaldi and Knutti 2007). Chandler (2013) develops a Bayesian statistical approach for taking these aspects into account to automatically weight the information from different models, with results that lead him to challenge weighting on the basis of historical performance. Chandler's approach is at the basis of a fisheries-related multiple model inference approach proposed by Spence *et al.* (2017); however their focus is on combining the results from various ecosystem models, each with predictions for numerous species, and hence has to address a level of complexity rather greater than the single-species-type example to be considered later in this dissertation.

Another example of weighting models in an MME is the "Reliability Ensemble Averaging" (REA) method described by Giorgi and Mearns (2002 and 2003). In 2002, this method was applied to an ensemble of 18 different Atmosphere-Ocean General Circulation Models (AOGCMs). The method allows a weighted average of the ensemble members taking two "reliability criteria" into account: model performance and model convergence. The model performance criterion measures the model's reliability as a function of the model bias in simulating present-day temperature. The bias is defined as the difference between simulated and observed mean temperature for a present-day period with higher bias reflecting lower model reliability. The model convergence criterion is a measure of the degree of goodness-of-fit of a given model, with the other models in terms of the distance of the change calculated by a given model from the REA average change, for example, the distance $D_{T,i} = [\Delta T_i - \tilde{\Delta T}]$ of the change in temperature calculated by model i, ΔT_i from the REA average change $\tilde{\Delta T}$. These criteria can be weighted and an uncertainty range around the REA average change can be determined. A quantitative measure of reliability for each model can be obtained by using this method in order to minimise the influence that outlier or poorly performing models can have on the overall ensemble results. In 2003, an extension of the REA method was presented which calculated the probability of regional climate change exceeding given thresholds. The reliability factor described above was used to estimate the probability of future climate change from the model ensemble.

A further example of a weighting method (described in detail in Appendix 4.C) is that in Sanderson *et al.* (2015b), where a distance metric (Euclidean distances amongst models and between each model and the observations) is developed that enables both models and observations to be represented as points in a multidimensional space. In a related paper, Sanderson *et al.* (2015a) use this distance metric, along with the CMIP5 multimodel archive, to demonstrate a model weighting scheme that accounts for both model skill (ability to model observed data) and model interdependence. Two different model weights are proposed. On the one hand, the uniqueness weighting is based on the distances between the model points in the multidimensional space, with closely related models being downweighted. On the other hand, the model quality weighting uses the distances between each of the models and the observations.

2.4 Discussion and comparison

Fisheries modelling is challenging because it is difficult to obtain abundance data and almost impossible to precisely determine population attributes such as natural mortality. This lack of data means that many assumptions must be made regarding the structure of the models and the parameters used to describe the fish populations. Climate modelling has similar challenges when it comes to modelling complex climate systems on different scales.

Regarding uncertainties related to the variability within the systems and to the models used to describe them, there is a major overlap between the two fields, which is why climate change ensembles are investigated in this dissertation. When it comes to model structure, both fields are subject to uncertainty regarding initial condition assumptions, how to parameterise the model and the values of the parameters. Even though there is rather more internal variability in climate systems than in fisheries, both fields must simplify their systems in order to model them, which leads to uncertainty. Implementation error in fisheries and scenario uncertainty in climate sciences are similar types of uncertainty related to future scenarios. Observation error occurs in some way whenever data are collected but it is more important of a consideration in fisheries than in climate change, due to the difficulties and expense of collecting data, than in climate change. Table 2.2 illustrates these similarities.

The relative importance of each of these sources of uncertainty varies between fields with regard to both prediction lead time and the spatial and temporal averaging scale. In climate change, for short time horizons (ten to twenty years), the main sources of uncertainty on a regional scale are model structure uncertainty and internal variability (Hawkins and Sutton 2009). Model and scenario uncertainty become the dominant sources of uncertainty at regional or larger scales for longer time horizons (Hawkins and Sutton 2009). In contrast, in most fisheries cases the dynamics are (taken to be) unchanged over time and the implementation error usually, but not always, has a small effect.

There is a common type of model ensemble used in both fisheries and climate change fields: the MME. Although the models that make up the ensembles are different, the idea of determining the skill of a model (its ability to replicate processes for which there are observations) is common between the fields. Both fields use Bayesian methods or weighted averages in order to integrate results over the individual models in MMEs. The terminology used in the two fields is contrasted in Table 2.3.

Models in an ensemble are, however, not fully independent. This is the case in both fisheries management and climate change. In climate sciences, this problem has, in some cases, been addressed by determining how "near" models are to one another and downweighting the models that are similar. The concept of weighting in relation to model "nearness" has not been considered extensively in fisheries, so that the application of this method is investigated using the South African hake resource as a case study. Sanderson *et al.* (2015a)'s method is described in more detail in Chapter 4.

Table 2.1: Revised RS grid for 2017 Southern Bluefin Tuna assessment (Parma *et al.* 2017).

Parameter	Value	Cumul N	Prior	Sampling
h[1]	0.60, 0.70, 0.8	3	Uniform	Prior
M_0[2]	0.35, 0.40, 0.45, 0.50	12	Uniform	ObjFn
M_{10}[3]	0.05, 0.085, 0.12	36	Uniform	ObjFn
Omega (ω)[4]	1	36	Uniform	Prior
CPUE	w0.5, w0.8	72	Uniform	Prior
CPUE age range	4-18, 8-12	144	0.67, 0.33	Prior
Psi (ψ)[5]	1.5, 1.75, 2.0	432	0.25, 0.5, 0.25	Prior

[1] steepness

[2],[3] natural mortality at age

[4] power in CPUE vs, abundance relationship

[5] power parameter on fecundity for the allometric relationship between fecundity and reproductive success

Table 2.2: Comparison of uncertainties in the fields of fisheries management and climate change.

Fisheries management	Description	Climate science	Description
Model structure error	Do not know which model represents system best	Model/response uncertainty	Do not know which model represents system best
Process error	Inability of simple models to describe complex processes	Internal variability	Naturally occurring fluctuations in the system
Implementation error	Catches not always exactly equal to TACs	Scenario uncertainty	Uncertainty in emission scenarios
Observation error	Data that are collected have errors	Observation error	Little focus on this but it will impact in cases where model parameters are estimated by fitting to data

Table 2.3: Comparison of model weighting terms in the fields of fisheries management and climate change.

Fisheries management	Description	Climate science	Description
Bayesian model averaging	Weights are Bayesian posterior probabilities	Bayesian model averaging	Weights are Bayesian posterior probabilities
Simple weighted averaging	Expert opinion taking into account each scenario's relative plausibility	Simple weighted averaging	Expert opinion taking into account each scenario's relative plausibility
Model fit to data (e.g. GCV score, AIC and BIC weights)	Measures of how well each model fits the data	Model convergence/ quality weighting (model skill)	Measures of how well each model fits the data
Model performance (e.g. AUC and TSS)	Measure of how well the model replicates well-known system processes for which observation data exists	Model performance (e.g. REA method)	Measure of how well the model replicates well-known climate processes and conditions for which observation data exists
Parameter value weighting (FIC)	An estimate of the mean squared error (MSE) associated with a model's estimate of a focus parameter	Probabilistic approach	Probability distributions applied to uncertain climate change parameter values
-	-	Uniqueness weighting	Measure of model interdependence

Chapter 3

South African hake fishery

3.1 Introduction

The South African hake fishery is used in this dissertation to provide a case study for an investigation into different methods of weighting models in an ensemble. The history of the fishery is detailed in this chapter, along with details about the Reference Case model, Reference Set and OMP-2014.

3.2 History of the South African hake fishery

There are three important hake species (*M. capensis*, *M. paradoxus* and *M. polli*) in the Southeast Atlantic (see Figure 3.1); these contributed 22 percent of the landings in this region in 2013 (FAO 2016). The bulk of the catches taken in this region come from the EEZs of three coastal countries: Angola, Namibia and South Africa (FAO 2016).

The South African hake resource consists of two species: the shallow-water Cape hake *M. capensis* and the deep-water Cape hake *M. paradoxus*. The hake fishery currently constitutes the bulk of the South African fishing industry (53% by value) (Durholtz *et al.* 2015). The hake is targeted by four distinct fisheries: the deep-sea trawl fishery (84% of the TAC), the inshore trawl and longline fisheries (6% of the TAC each) and the handline fishery (about 3% of the TAC allocation) with a total 2016 TAC of 147 500 tonnes (SADSTIA 2016). The deep-sea trawling industry employs an estimated 7 050 workers and has annual sales in excess of R5 billion (SADSTIA 2016).

During the late 1800s, the hake catch was only incidental to that of Agulhas sole (*Austroglossus pectoralis*), which was targeted by the developing demersal trawl fishery off South Africa (De Jongh 1974). However, trawlers started to target hake after World War 1 with annual catches of about 1 000 tonnes (Payne and Punt 1992). Catches increased slowly at first, but then more rapidly after World War 2, reaching 100 thousand tonnes in 1954 (Chalmers 1976). The mid-1960s saw rapidly growing fishing effort by foreign fleets (Payne 1989), with annual catches peaking in the early 1970s at about 300 thousand tonnes per year (Rademeyer *et al.* 2008) (see Table 3.1). The increased foreign activity led to a decrease in catch per unit effort (CPUE), which in the early 1970s threatened the economic viability of the local industry (Payne and Punt 1995).

The Du Plessis Commission was appointed to address this problem, as part of its wider brief to inquire into, report on and make recommendations regarding all aspects of the fishing industry along the coasts of the Republic of South Africa and South West Africa. One of their specific objectives was to investigate the desirability and nature of the ways and means to restrict the operation of foreign fishing vessels along those coasts (Du Plessis *et al.* 1971). In its 1971 Report, the Commission noted the efforts made by the various trawling companies to acquire modern vessels but considered that the South African trawler fleet fell short of the desired level of technical efficiency (Du Plessis *et al.* 1971). Inadequate harbour facilities also seemed to have hampered the renewal of the trawler fleet (Du Plessis *et al.* 1971). In paragraph 274 of its Report, the Commission recommended that a programme be launched to improve the technical efficiency of the fleet, and that an investigation be undertaken to determine its optimum size and composition, the path to be followed to realise this optimum fleet, and the role (financial or other) which the State should play in the renewal of the fleet (Du Plessis *et al.* 1971). The report suggested that the authorities undertake this study in consultation with the trawling industry (Du Plessis *et al.* 1971).

The following year, declining abundance indices and rapidly rising catches led to the formation of the International Commission for the Southeast Atlantic Fisheries (ICSEAF) (Andrew and Butterworth 1987). The reduced catch rate (see Table 3.2), caused mainly by the increase in foreign fishing, led ICSEAF to introduce an observer programme, allocate quotas to member nations and change mesh size regulations (Hutton 2003).

Around this time, during the negotiations leading up to the adoption of the LOSC (called UNCLOS III, i.e. The Third UN Convention on the Law of the Sea, from 1973 to 1982) many States, including Angola and Mozambique, were extending their exclusive fishing jurisdiction to 200 nm (Vrancken 2011). To protect its own fishery, South Africa also extended its exclusive fishing zone (EFZ) to 200 nm in 1977 (Government Printer 1977)[5]. After the extension of the EFZ, which forced foreign fleets to withdraw from South African waters (Hutton 2003), South Africa took over control of the fishery from ICSEAF (Butterworth and Rademeyer 2005). The resulting lack of foreign activity caused the annual catches to decrease over the late 1970s to a range of about 120–150 thousand tonnes per year (Rademeyer *et al.* 2008) (see Table 3.1). In 1979, the South African Government, in association with the industry, decided on a rebuilding strategy and introduced individual quotas to companies, with the overall TAC being based on recommendations made by ICSEAF (Hutton 2003). The rebuilding strategy, which included the cooperation of the industry, was set in place in 1982 and resulted in a halt to the declining catch rates and in annual hake catches remaining fairly constant from 1982 to 1991 with an annual average of 138 000 tonnes per year for the West and South coast fisheries combined (Hutton 2003) (see Table 3.1).

In 1986, the Diemont Commission recommended that the Minister of Environmental Affairs determine the TAC from time to time, after consultation (Diemont *et al.* 1986). In terms of allocating the TAC to different groups as quotas, the Commission took the view that a Quota Board should be established to allocate individual quotas (Diemont *et al.* 1986), with specific recommendations regarding the allocation of quotas set out in paragraph 2.55 of its Report (Diemont *et al.* 1986). The Commission highlighted the desirability that the Quota Board be independent of the Minister in order to handle the sensitive issue of allocation of scarce resources (Cole 1988).

Based on the recommendations of the Diemont Commission, the Sea Fishery Act 12 of 1988 was adopted (Department of Environmental Affairs 1988). In terms of the Act, the Minister was responsible for appointing a

[5]When the LOSC was adopted, it went further than the EFZs by allowing States to claim exclusive economic zones (EEZs). The South African fishing zone was converted into an EEZ by Section 7(1) of the Maritime Zones Act, 1994 (Act 15 of 1994) (Government Printer 1994)

Sea Fisheries Advisory Committee (SFAC) and a Quota Board using the extensive discretionary powers granted to him (Hutton 2003).

In the 1990s, the hake CPUE showed a steady upward trend (Butterworth 2010). It was, however, found that the trend was misleading. The increased catch rates were largely a result of the average size of trawling vessels increasing, which gave them greater fishing power, where this had not been taken into account adequately in calculating the CPUE. In addition, in the late 1990s, the research survey vessel broke down after two successive surveys had yielded very large abundance estimates. The next surveys had to be conducted using a different vessel which made the results difficult to compare with those from the surveys conducted previously. When the original survey vessel returned, the abundance estimates from its new surveys indicated appreciably less hake than at the end of the 1990s. The mid 2000s saw a 30-40% drop in CPUE which by 2006 had resulted in severely reduced profit margins (Butterworth 2010). For this reason, the industry was prepared to make short term cuts in TACs with the objective of increasing CPUE by 50% (Rademeyer 2012).

Since the start of the 21st century, the catches have generally been very close to the TACs, which hardly differed from the scientific recommendations (Rademeyer 2012). This means that the implementation error in the management of the fishery has been small. More recently, total allowable effort (TAE) restrictions were introduced for the deep-sea fishery (SADSTIA 2016). These effort restrictions are relatively generous with each trawler being licensed to fish for a limited number of days per year; the goal is to ensure that the deep-sea fishing fleet does not grow too large for the resources available. The licences are further aimed at preventing the targeting of bycatch species once hake quotas have been filled, as well as limiting the potential for illegal (beyond quota) catches (SADSTIA 2016).

During most of the last century, quantitative assessment methods treated the two different, although morphologically similar, species found in South African waters as one (Rademeyer *et al.* 2008). This was because the catch-and-effort statistics collected from the fishery were not species-disaggregated (Punt 1994), as a result of a lack of personnel such as observers on board to continuously distinguish between the two species (Rademeyer *et al.* 2008). In 1993, simulation studies (Punt 1993) showed that this was not problematic, provided that the species composition and the age-selectivity pattern of the fishery remained unchanged. By then, OMPs were being used as the basis to provide TAC advice, after the TAC recommendations had earlier been based on steady-state surplus production models and, later, on dynamic surplus production models (Butterworth and Andrew 1984).

OMP-2007 was based on the first fully species-disaggregated coast-combined baseline assessment. In that assessment, the two hake species are treated separately, although within the same model to be able to take data that are not species-disaggregated into account, e.g. commercial catches-at-age (Rademeyer *et al.* 2008). In the process, species-splitting algorithms for catch and CPUE data are used where necessary (Rademeyer *et al.* 2008). These algorithms involve the use of size-based species proportion-at-depth relationships for the West and South coasts (determined from data collected on the abundance surveys) to split the offshore trawl fleet catches by species (Gaylard and Bergh 2004). Moreover, the South and West Coast components of each species are together taken to comprise a single stock, despite being treated as two separate populations earlier (Rademeyer *et al.* 2008). In addition, the stock structure and possible interchange of the populations of both species shared with Namibia is not clearly understood. For that reason, the South African populations are currently assessed separately from the Namibian populations (Rademeyer *et al.* 2008).

Two very different depletion levels were estimated by the split species assessments on which OMP-2007 was based, with *M. paradoxus* well below (only about one third) and *M. capensis* well above (more than double) their

maximum sustainable yield levels (MSYLs) (Rademeyer *et al.* 2008). This information was unexpected since, from the then previous assessment (West and South coasts separate and species-aggregated), the West Coast component seemed to have recovered and almost reached MSYL, while the South Coast component seemed to be well above MSYL (Butterworth and Rademeyer 2005). Probably the main reason for the much more depleted status estimated for *M. paradoxus* was the cumulative historical *M. paradoxus* catches that had likely been about double those of *M. capensis*. This was a consequence of the rapid increase in catches in the 1960s and 1970s (Durholtz *et al.* 2015). The newly-revealed *M. paradoxus* depletion level caused much concern and, for that reason, the primary objective of OMP-2007 became to recover the *M. paradoxus* stock to MSYL over the next 20 years (Rademeyer 2012).

OMP-2007 was developed taking several possible scenarios or OMs for the underlying dynamics of the resource into account. These were constructed to correspond to different assessments of the resource based upon different assumptions or input parameter values (Rademeyer *et al.* 2008). The scenarios included were considered to be highly plausible with their differences also having major impacts on the results (Rademeyer *et al.* 2008). These OMs were used to determine how the resource would respond to different future levels of exploitation (Rademeyer *et al.* 2008).

A Reference Set (RS) - a core set of 24 OMs, which included the major uncertainties (natural mortality, species split of the catches and the stock-recruitment relationships' steepness parameters) - was used in the initial phase of Candidate Management Procedure (CMP) testing for OMP-2007 (Rademeyer *et al.* 2008).

This process was used to provide TAC recommendations. The TAC values for the two species were computed separately, but the TAC recommended by the OMP was for the two species combined, since it is difficult to identify the species on board (Rademeyer 2012). This total TAC recommended by the OMP was then divided into fixed proportions among the various fleets according to the rights allocations to the different sectors at the time (Rademeyer 2012).

For the next revision, the OMs used to develop OMP-2011 introduced gender-disaggregation, since there are definite differences in somatic growth rates between males and females (Durholtz *et al.* 2015). These differences in growth rates can, for example, cause younger females to be mistakenly grouped with older males as having the same age because they are the same size. The additional complication of adding gender-disaggregation was deemed necessary due to the effect that the incorrect age groupings might have on the estimation of values and trends in the hake abundance. The OMs estimated gender-specific growth curve parameters in the model by fitting to the annual age-length keys. These refinements, along with additional survey and CPUE data showing an upward trend, led to the assessments estimating a *M. paradoxus* depletion level of 16% relative to pristine spawning biomass in 2009, in contrast to the 10% estimated in 2006. The successful implementation of the 2007 and 2011 OMPs resulted in the 2012 TAC (144 670 tonnes) being almost back at the 2006 level (of 150 000 tonnes) after having fallen to 118 578 tonnes in 2009 (Anderson *et al.* 2014, Durholtz *et al.* 2015).

OMP-2014 has been used to set TACs from 2015 to 2018. One of the main areas of uncertainty covered by the RS, consisting of 11 OMs, is the "center-year for the species preponderance change in the catch" (Rademeyer and Butterworth 2014c). This area of uncertainty is considered important because the assessments used in the development of OMP-2011 showed that depletion estimates of the *M. paradoxus* are sensitive to assumptions about how the pre-1978 catches are split between the two species (Rademeyer and Butterworth 2014c). The other two main areas of uncertainty are natural mortality and stock-recruitment relationships (Rademeyer and Butterworth 2014c). More details about OMP-2014 are provided in the next section of this chapter.

3.3 OMP-2014

3.3.1 Hake assessment data

There are four main types of data which are available for the assessment of the South African hake resource. These are the annual catches (by mass), survey biomass and commercial catch-per-unit-effort (CPUE) based abundance indices, catches-at-length and age-length keys. These data types are discussed in general terms below. Since this dissertation utilises assessment results from Rademeyer and Butterworth (2014b), the data presented here go as far as 2013 only to correspond to those used for that analysis.

3.3.1.1 Annual catches

Commercial catch by mass are available from the beginning of the fishery and have been disaggregated by fleet where possible. Table 3.1 provides a list of the annual catch data for all fleets. Since the commercial fishery does not separate catch by species, and the species-disaggregated assessment model requires catch-by-species information, the catches are split external to the model. A detailed explanation of the splitting procedure for the offshore trawl fleet can be found in Gaylard and Bergh (2004).

3.3.1.1.1 Offshore trawl fleet

Deep-sea offshore trawling currently operates on the West Coast at depths greater than 180m with restrictions prohibiting trawling at depths less than 110m on the South Coast. The offshore fleet takes over 80% of the total amount by mass of the hake catch.

Starting in 1978, depth information became available for catches which allowed algorithms to be used to split offshore catches by species. The algorithms (details may be found in Glazer (2013)) use size-based proportion-by-depth information from research surveys to fit logistic forms to the proportion of *M. capensis* found at various depths for different size classes. Separate algorithms are used for the West and South Coast with respective proportions of *M. capensis* and *M. paradoxus* around the coast being inferred from the size-composition, depth, year and longshore position of the data collected on the surveys. For the years before 1978, the annual proportion of *M. capensis* in the catch is assumed to follow a logistic function with time, starting at unity in 1917 when the fishery commenced and operated close to the coast, and decreasing to match (in 1978) the average proportion over 1978-1982.

Over a period centred at some year between 1950 and 1970, trawling moved from the shallower waters around Cape Town into deeper waters off the Western Cape. When this happened, catch would have shifted from predominantly *M. capensis* to predominantly *M. paradoxus*; various assumptions for the central year when this transition is assumed to have occurred are considered for the assessment model and are detailed in Appendix 3.B.

3.3.1.1.2 Inshore trawl fleet

The inshore trawl fleet operates mainly from Port Elizabeth and Mossel Bay and catches very few *M. paradoxus* since it fishes largely in depths less than 110m. It is for this reason that the assessment model assumes that the catch by this fleet consists entirely of *M. capensis*.

3.3.1.1.3 Longline fleet

Developed in the late 1980s and 1990s, the longline fishery operates around the entire coast of South Africa. Since 1984, catch data are available for the West and South Coast; these have been separated by species based on information on the recent species composition of these catches.

3.3.1.1.4 Handline fleet

The handline fleet began operations in the late 1980s, originating mainly from Plettenberg Bay on the South Coast and fishing at depths of about 100m. As with the inshore trawl fleet, the catch is almost exclusively *M. capensis*, so that the assessment model assumes that catches consist of *M. capensis* only.

3.3.1.2 Abundance indices

There are six commercial abundance indices based on catch-per-unit-effort (CPUE) data, with these CPUE indices assumed to be proportional to abundance as is conventional. The historical CPUE series for each of the West and South coasts, and the GLM-standardised CPUE series for each species and each coast, are listed in Table 3.2. Details of the GLM standardisation can be found in Rademeyer *et al.* (2014).

There are also biomass indices available from research surveys which are independent of commercial operations. They are available from the South Coast spring/autumn and the West Coast winter/summer research surveys, and can be found in Tables 3.3a and 3.3b. These indices are useful because the survey vessels (mostly) remain unchanged over time and the design and timing of the surveys is controlled. It is for this reason that survey biomass indices are considered to be less biased (potentially) than CPUE indices. Survey biomass estimates might, however, be expected to be less precise than CPUE indices since surveys typically take place once or twice a year only, whereas the commercial CPUE series are obtained from data averaged over a year and from a large number rather than from a single vessel only.

3.3.1.3 Catches-at-length

There are two distinct sources of species-aggregated catch-at-length data: research surveys (Table 3.4) and commercial data (Table 3.5). These data can be found in Tables 3.4a to 3.4h (survey) and Tables 3.5a to 3.5e (commercial) of Ross-Gillespie (2016).

3.3.1.4 Age-length keys

Commercial catch-at-age data are often inputs to assessment models, and may be obtained indirectly from catch-at-length data using species-aggregated age-length keys (ALKs). However in this case the assessment model is fitted directly to these ALKs and to length frequency information which (for later years) is available for each sex and species. Due to gear selectivity and mortality, relatively small numbers of fish in the smallest and largest age classes are caught. This can lead to relatively large errors (in terms of variance) in these data. In order to reduce this effect, “minus-” and “plus-age groups” (obtained by summing the data over the ages below “age-minus” and above “age-plus” repsectively) are used in the assessment. These data may also be biased due to age-reading error amongst readers, and a reader-calibration process is used to take this into account.

3.3.2 Assessment method

The assessment is a gender-disaggregated Statistical Catch-at-Age (SCAA) model, which is fitted directly to ALKs and length frequencies. The model considers the two hake species to be two independent stocks and is fitted to both species-disaggregated and species combined data with a distinction being made between the West and South coasts. The data used as input to the Reference Case (RC) are given in Section 3.3.1 of this chapter, and the general specifications and equations of the model are detailed in Appendix 3.A along with a number of key choices for implementation of the methodology. Details of the log-likelihood function contributions are also given. The total negative log-likelihood function is minimised using Quasi-Newton minimisation[6].

3.3.3 Operating Models and OMPs

A final RS of 11 OMs was chosen to cover the main uncertainties when developing OMP-2014: natural mortality, stock-recruitment relationships and centre years for change from *M. capensis* to *M. paradoxus* preponderance in the catch. Detailed specifications on the RS can be found in Appendix 3.B.

These OMs were used in testing the CMPs. Four final CMPs (Rademeyer and Butterworth 2014b) were identified and were distinguished by two different target average TACs for the next decade, and by whether or not the TAC was to be fixed for the next two years (see Table 3.6). The final CMP chosen for OMP-2014 was $CMPfinal2_{135}$.

A number of performance statistics were evaluated under the RS for the four final CMPs (see Table 3.7 for these final CMP statistics). The performance statistics shown there were not the only ones considered, but were those that were focused upon to make the final selection.

In the process of testing the CMPs, a wider range of scenarios was included in the form of robustness tests (details may be found in Rademeyer and Butterworth (2014b)). The three most influential of the scenarios which were considered were industry vessels being used for future demersal surveys, an undetected increase in CPUE catchability q and a future change in the carrying capacity. Sensitivities to some of the uncertainty factors other than those considered in the RS are also investigated (see Rademeyer and Butterworth (2014a) for details).

3.3.4 OMP specifications and Projections

The empirical algorithm underlying the 2014 Operational Management Procedure (OMP-2014), which provides TAC recommendations for the two South African hake resources, calculates the TAC in relation to an aggregate abundance index that combines CPUE and survey abundance estimates compared to a target level for that index. The main equations describing the OMP are listed below, with the tuning parameters listed in Table 3.8. More details can be found in Rademeyer *et al.* (2014).

The 2014 OMP formula is:

$$TAC_{y+1} = C^{para}_{y+1} + C^{cap}_{y+1} \tag{3.3.1}$$

[6]Quasi-Newton minimisation implemented using AD Model BuilderTM, Otter Research, Ltd.

with

$$C_{y+1}^{spp} = b^{spp}(J_y^{spp} - J_0^{spp}) \tag{3.3.2}$$

where

TAC_y is the total TAC recommended for year y,

C_y^{spp} is the intended species-disaggregated TAC for species *spp* year y,

J_0^{spp} and b^{spp} are tuning parameters (see Table 3.8), and

J_y^{spp} is a measure of the immediate past level in the abundance indices for species *spp* that is available to use for calculations for year y.

Measure of recent abundance level

The measures of the immediate past level J_y^{spp} for the abundance indices are computed as follows (note that these J indices reflect averages over the most recent three years for which the data in question are available):

$$J_y^{para} = \frac{1.0J_y^{WC\_CPUE,para} + 0.75J_y^{SC\_CPUE,para} + 0.5J_y^{WC\_surv,para} + 0.25J_y^{SC\_surv,para}}{2.5} \tag{3.3.3}$$

$$J_y^{cap} = \frac{1.0J_y^{WC\_CPUE,cap} + 0.75J_y^{SC\_CPUE,cap} + 0.5J_y^{WC\_surv,cap} + 1.0J_y^{SC\_surv,cap}}{3.25} \tag{3.3.4}$$

with

$$J_y^{WC/SC\_CPUE,spp} = \sum_{y'=y-4}^{y-2} I_y^{WC/SC\_CPUE,spp} / \sum_{y=2010}^{2012} I_y^{WC/SC\_CPUE,spp} \tag{3.3.5}$$

$$J_y^{WC/SC\_surv,spp} = \sum_{y'=y-3}^{y-1} I_y^{WC/SC\_surv,spp} / \sum_{y=2011}^{2013} I_y^{WC/SC\_surv,spp} \tag{3.3.6}$$

Thus the weighting of the different indices (denoted by I_y^i) is taken to be the same as for OMP-2010 (Rademeyer *et al.* 2010), and the normalization is such that a value of $J = 1$ reflects resource abundance at about the same level as in 2011/2012.

Constraints on the inter-annual TAC change

The maximum allowable annual increase in the TAC is 10%, and the maximum allowable annual decrease in the TAC is 5% unless the *M. paradoxus* average biomass index falls too low, in which case the maximum allowable annual decrease becomes:

$$MaxDecr_y = \begin{cases} 5\% & \text{if } J_y \geq J^{thresh1} \\ \textit{linear between } x\% \textit{ and } 5\% & \text{if } J^{thresh2} \leq J_y < J^{thresh1} \\ x\% & \text{if } J_y < J^{thresh2} \end{cases} \tag{3.3.7}$$

where x , $J^{thresh1}$ and $J^{thresh2}$ are tuning parameters (see Table 3.8).

Two further constraints are included in OMP-2014:

1. An upper cap on the TAC is imposed, so that the TAC cannot exceed 150 000t.
2. The TACs for 2015 and 2016 are fixed at 147 500t.

Details regarding Exceptional Circumstances provisions, the GLM CPUE standardisation approach and survey details can be found in Rademeyer *et al.* (2014).

Projections (95%, 90% and 80% PIs and medians) for the RS under OMP-2014, also compared with the resource abundance index data for the year following those for which data were available when conditioning the OMs, are shown in Figure 3.2. Medians and lower 5%iles for total catch, spawning biomass (relative to MSYL level), CPUE (relative to 2013) and effort (relative to 2010) for the RS under the final four CMPs are shown in Figure 3.3, with 95, 90 and 80% PIs and medians for a series of performance statistics for the CMP chosen (OMP-2014) under the RS in Figure 3.4.

Table 3.1: Species-disaggregated commercial catches (in thousand tonnes), by fleet, of South African hake from the West (WC) and South (SC) coasts for the period 1917-2013 (Rademeyer and Butterworth 2014d).

Year	*M. paradoxus*				*M. capensis*					
	Offshore		Longline		Offshore		Inshore	Longline		Handline
	WC	SC	WC	SC	WC	SC	SC	WC	SC	SC
1917	-	-	-	-	1.000	-	-	-	-	-
1918	-	-	-	-	1.100	-	-	-	-	-
1919	-	-	-	-	1.900	-	-	-	-	-
1920	-	-	-	-	-	-	-	-	-	-
1921	-	-	-	-	1.300	-	-	-	-	-
1922	-	-	-	-	1.000	-	-	-	-	-
1923	-	-	-	-	2.500	-	-	-	-	-
1924	-	-	-	-	1.500	-	-	-	-	-
1925	-	-	-	-	1.900	-	-	-	-	-
1926	-	-	-	-	1.400	-	-	-	-	-
1927	-	-	-	-	0.800	-	-	-	-	-
1928	-	-	-	-	2.600	-	-	-	-	-
1929	-	-	-	-	3.800	-	-	-	-	-
1930	-	-	-	-	4.400	-	-	-	-	-
1931	-	-	-	-	2.800	-	-	-	-	-
1932	-	-	-	-	14.300	-	-	-	-	-
1933	-	-	-	-	11.100	-	-	-	-	-
1934	-	-	-	-	13.800	-	-	-	-	-
1935	-	-	-	-	15.000	-	-	-	-	-
1936	-	-	-	-	17.700	-	-	-	-	-
1937	-	-	-	-	20.200	-	-	-	-	-
1938	-	-	-	-	21.100	-	-	-	-	-
1939	-	-	-	-	20.000	-	-	-	-	-
1940	-	-	-	-	28.600	-	-	-	-	-
1941	-	-	-	-	30.600	-	-	-	-	-
1942	0.001	-	-	-	34.499	-	-	-	-	-
1943	0.001	-	-	-	37.899	-	-	-	-	-
1944	0.002	-	-	-	34.098	-	-	-	-	-
1945	0.004	-	-	-	29.196	-	-	-	-	-
1946	0.011	-	-	-	40.389	-	-	-	-	-
1947	0.021	-	-	-	41.379	-	-	-	-	-
1948	0.059	-	-	-	58.741	-	-	-	-	-
1949	0.113	-	-	-	57.287	-	-	-	-	-
1950	0.275	-	-	-	71.725	-	-	-	-	-
1951	0.662	-	-	-	88.838	-	-	-	-	-
1952	1.268	-	-	-	87.532	-	-	-	-	-
1953	2.558	-	-	-	90.942	-	-	-	-	-
1954	5.438	-	-	-	99.962	-	-	-	-	-
1955	10.924	-	-	-	104.476	-	-	-	-	-

Continued on next page ...

Table 3.1: *... continued from previous page*

Year	*M. paradoxus*				*M. capensis*					
	Offshore		Longline		Offshore		Inshore	Longline		Handline
	WC	SC	WC	SC	WC	SC	SC	WC	SC	SC
1956	19.581	-	-	-	98.619	-	-	-	-	-
1957	34.052	-	-	-	92.348	-	-	-	-	-
1958	51.895	-	-	-	78.805	-	-	-	-	-
1959	76.609	-	-	-	69.391	-	-	-	-	-
1960	100.490	-	-	-	59.410	-	1.000	-	-	-
1961	104.009	-	-	-	44.691	-	1.308	-	-	-
1962	109.596	-	-	-	38.004	-	1.615	-	-	-
1963	129.966	-	-	-	39.534	-	1.923	-	-	-
1964	126.567	-	-	-	35.733	-	2.231	-	-	-
1965	159.704	-	-	-	43.296	-	2.538	-	-	-
1966	154.109	-	-	-	40.891	-	2.846	-	-	-
1967	139.973	7.086	-	-	36.727	7.100	3.154	-	-	-
1968	113.890	13.958	-	-	29.710	13.950	3.462	-	-	-
1969	131.023	18.982	-	-	34.077	18.948	3.769	-	-	-
1970	113.124	11.876	-	-	29.376	11.847	4.077	-	-	-
1971	160.384	15.078	-	-	41.616	15.037	4.385	-	-	-
1972	193.694	23.382	-	-	50.239	23.314	4.692	-	-	-
1973	125.292	36.232	-	-	32.490	36.124	5.000	-	-	-
1974	97.674	45.496	-	-	25.326	45.357	10.056	-	-	-
1975	71.165	33.783	-	-	18.452	33.680	6.372	-	-	-
1976	114.268	26.005	-	-	29.626	25.925	5.740	-	-	-
1977	81.260	18.515	-	-	21.068	18.457	3.500	-	-	-
1978	107.701	4.937	-	-	19.812	2.648	4.931	-	-	-
1979	101.890	3.575	-	-	31.633	3.345	6.093	-	-	-
1980	105.483	3.676	-	-	28.045	2.784	9.121	-	-	-
1981	95.330	1.767	-	-	25.601	3.719	9.400	-	-	-
1982	88.933	5.057	-	-	24.417	6.300	8.089	-	-	-
1983	74.173	7.034	0.126	-	20.260	5.482	7.672	0.104	-	-
1984	86.045	5.718	0.200	0.005	25.210	5.217	9.035	0.166	0.011	-
1985	98.283	12.694	0.638	0.091	26.788	7.322	9.203	0.529	0.201	0.065
1986	107.907	11.539	0.753	0.094	25.898	4.427	8.724	0.625	0.208	0.084
1987	96.162	10.536	1.952	0.110	21.363	5.148	8.607	1.619	0.243	0.096
1988	83.606	8.664	2.833	0.103	22.976	5.852	8.417	2.350	0.228	0.071
1989	85.298	9.039	0.158	0.010	21.961	9.873	10.038	0.132	0.022	0.137
1990	84.969	13.622	0.211	-	18.668	9.169	10.012	0.175	-	0.348
1991	89.371	15.955	-	0.932	17.079	6.119	8.206	-	2.068	1.270
1992	86.777	22.368	-	0.466	16.510	4.094	9.252	-	1.034	1.099
1993	105.114	12.472	-	-	12.951	1.789	8.870	-	-	0.278
1994	106.287	8.588	0.882	0.194	17.580	2.464	9.569	0.732	0.432	0.449
1995	102.877	5.395	0.523	0.202	18.020	1.755	10.630	0.434	0.448	0.756
1996	110.460	11.080	1.308	0.568	18.715	2.209	11.062	1.086	1.260	1.515
1997	103.035	13.651	1.410	0.582	14.119	2.185	8.834	1.170	1.290	1.404

Continued on next page ...

Table 3.1: *... continued from previous page*

Year	*M. paradoxus*				*M. capensis*					
	Offshore		Longline		Offshore		Inshore	Longline		Handline
	WC	SC	WC	SC	WC	SC	SC	WC	SC	SC
1998	113.083	11.703	0.505	0.457	14.570	2.450	8.283	0.419	1.014	1.738
1999	89.147	13.435	1.532	1.288	14.614	1.912	8.595	1.272	2.856	2.749
2000	97.417	9.920	2.706	3.105	20.285	3.610	10.906	2.000	1.977	5.500
2001	101.990	11.016	2.045	0.370	15.606	5.141	11.836	1.750	1.347	7.300
2002	91.720	15.445	4.469	1.585	13.211	3.140	9.581	2.391	2.546	3.500
2003	95.143	21.107	3.305	1.252	10.233	3.926	9.883	2.526	3.078	3.000
2004	86.916	30.746	2.855	1.196	11.315	4.024	10.004	2.297	2.731	1.600
2005	87.540	25.051	3.091	0.472	7.727	4.195	7.881	2.773	3.270	0.700
2006	83.840	22.133	3.241	0.485	9.657	2.494	5.524	2.520	3.227	0.400
2007	96.332	15.825	2.512	3.021	12.537	1.420	6.350	2.522	2.522	0.400
2008	88.290	14.940	2.255	0.809	11.085	2.567	5.496	1.937	1.893	0.231
2009	69.716	13.269	2.410	1.069	10.783	2.431	5.639	2.828	2.520	0.265
2010	70.156	17.863	2.045	0.370	9.738	1.649	5.472	1.750	1.347	0.275
2011	76.744	20.447	3.261	0.905	15.505	1.543	6.013	2.705	2.009	0.185
2012	82.531	19.204	3.582	0.573	11.978	1.751	3.223	2.972	1.272	0.008
2013	101.350	23.583	4.399	0.704	14.709	2.151	3.958	3.650	1.562	0.010

Table 3.2: West and South coast historical (ICSEAF 1989) and GLM standardized CPUE data (Glazer 2013). The historical data are available for the two species combined only but from 1978 onwards, the data are split by species for *M. paradoxus* and *M. capensis*.

	ICSEAF CPUE (tonnes/hour)			GLM CPUE (kg/min)			
	Species combined			*M. paradoxus*		*M. capensis*	
Year	WC	SC	Year	WC	SC	WC	SC
1955	17.31	-	1978	4.20	1.09	0.74	1.68
1956	15.64	-	1979	4.16	1.08	1.21	1.84
1957	16.47	-	1980	3.86	1.59	1.08	2.07
1958	16.26	-	1981	3.85	1.03	1.11	2.01
1959	16.26	-	1982	3.79	1.31	0.95	1.99
1960	17.31	-	1983	4.08	1.43	1.28	2.46
1961	12.09	-	1984	4.17	1.55	1.35	2.84
1962	14.18	-	1985	4.88	2.24	1.49	3.45
1963	13.97	-	1986	4.25	2.18	1.22	2.87
1964	14.60	-	1987	3.50	1.94	1.07	2.63
1965	10.84	-	1988	3.46	1.60	0.96	2.79
1966	10.63	-	1989	3.74	1.57	1.03	3.00
1967	10.01	-	1990	4.02	2.34	0.87	3.59
1968	10.01	-	1991	4.37	2.32	1.08	3.24
1969	8.62	1.28	1992	3.81	2.72	1.32	2.96
1970	7.23	1.22	1993	3.89	2.25	1.24	2.13
1971	7.09	1.14	1994	4.16	1.81	1.58	2.88
1972	4.90	0.64	1995	3.63	1.39	1.63	2.71
1973	4.97	0.56	1996	3.94	1.99	1.89	2.50
1974	4.65	0.54	1997	3.52	2.28	1.64	1.82
1975	4.66	0.37	1998	3.93	1.93	1.87	2.09
1976	5.35	0.40	1999	3.19	2.20	1.72	2.00
1977	4.84	0.42	2000	2.84	1.67	1.61	2.22
			2001	2.30	1.65	1.10	1.64
			2002	2.23	1.41	1.06	1.84
			2003	2.64	1.93	0.90	2.07
			2004	2.20	1.52	0.81	1.65
			2005	2.19	1.34	0.58	1.48
			2006	2.38	1.46	0.62	1.03
			2007	2.92	1.53	0.60	0.98
			2008	3.23	1.65	0.81	1.56
			2009	3.23	2.05	1.42	2.89
			2010	3.54	2.25	1.22	2.22
			2011	3.30	2.62	1.47	2.79
			2012	2.92	2.17	1.24	1.62

Table 3.3a: Survey abundance estimates and associated standard errors (in parentheses) in thousand tonnes for ***M. paradoxus*** for the depth range 0-500m for the West Coast and for the South Coast. Surveys were mostly conducted by the research vessel *Africana* to which a distinction between old and new gear pertains. Values in bold are for the surveys conducted by the *Africana* with the new gear (Fairweather 2012).

	West Coast				South Coast			
Year	Summer		Winter		Spring (Sep)		Autumn (Apr/May)	
1985	166.294	(35.299)	264.839	(52.949)	-	-	-	-
1986	196.111	(36.358)	172.477	(24.122)	13.758	(3.554)	-	-
1987	284.805	(53.101)	195.482	(44.415)	21.554	(4.605)	-	-
1988	158.758	(27.383)	233.041	(64.003)	-	-	30.316	(11.104)
1989	-	-	468.780	(124.830)	-	-	-	-
1990	282.174	(78.945)	226.862	(46.007)	-	-	-	-
1991	327.020	(82.180)	-	-	-	-	26.638	(10.460)
1992	226.687	(32.990)	-	-	-	-	24.304	(15.195)
1993	334.151	(50.234)	-	-	-	-	198.849	(98.452)
1994	330.270	(58.319)	-	-	-	-	111.469	(34.627)
1995	324.554	(80.357)	-	-	-	-	55.068	(22.380)
1996	430.908	(80.604)	-	-	-	-	85.546	(25.484)
1997	569.957	(108.200)	-	-	-	-	135.192	(51.031)
1998	-	-	-	-	-	-	-	-
1999	569.364	(114.536)	-	-	-	-	321.478	(113.557)
2000	-	-	-	-	-	-	-	-
2001	-	-	-	-	19.929	(9.956)	-	-
2002	267.487	(35.068)	-	-	-	-	-	-
2003	411.177	(69.431)	-	-	**88.442**	(36.051)	108.857	(37.528)
2004	**259.527**	(56.021)	-	-	**63.900**	(17.894)	**48.898**	(20.343)
2005	**286.416**	(39.849)	-	-	-	-	**26.605**	(7.952)
2006	315.310	(49.490)	-	-	72.415	(15.500)	34.799	(8.325)
2007	**397.049**	(71.564)	-	-	**52.287**	(19.231)	**129.646**	(60.661)
2008	**246.542**	(51.973)	-	-	**24.816**	(8.775)	**39.505**	(11.408)
2009	**330.235**	(28.526)	-	-	-	-	**102.834**	(28.670)
2010	589.533	(85.686)	-	-	-	-	169.560	(67.650)
2011	**347.082**	(92.540)	-	-	-	-	**24.105**	(7.089)
2012	**377.515**	(50.690)	-	-	-	-	-	-
2013	-	-	-	-	-	-	-	-

Table 3.3b: Survey abundance estimates and associated standard errors (in parentheses) in thousand tonnes for ***M. capensis*** for the depth range 0-500m for the West Coast and for the South Coast. Surveys were mostly conducted by the research vessel *Africana* to which a distinction between old and new gear pertains. Values in bold are for the surveys conducted by the *Africana* with the new gear (Fairweather 2012).

	West Coast				South Coast			
Year	Summer		Winter		Spring (Sep)		Autumn (Apr/May)	
1985	125.028	(22.719)	181.487	(27.476)	-	-	-	-
1986	117.810	(23.636)	119.587	(18.489)	121.197	(16.625)	-	-
1987	75.693	(10.241)	87.391	(11.198)	159.088	(17.233)	-	-
1988	66.725	(10.765)	47.120	(9.568)	-	-	165.939	(21.871)
1989	-	-	323.833	(67.295)	-	-	-	-
1990	455.798	(135.237)	157.800	(23.561)	-	-	-	-
1991	77.357	(14.995)	-	-	-	-	274.298	(44.395)
1992	95.407	(11.744)	-	-	-	-	138.085	(15.357)
1993	92.598	(14.589)	-	-	-	-	158.340	(13.733)
1994	121.257	(35.951)	-	-	-	-	160.555	(23.701)
1995	199.142	(26.812)	-	-	-	-	236.025	(31.840)
1996	83.337	(9.285)	-	-	-	-	244.410	(25.107)
1997	257.293	(46.056)	-	-	-	-	183.087	(18.906)
1998	-	-	-	-	-	-	-	-
1999	196.992	(32.059)	-	-	-	-	191.203	(14.952)
2000	-	-	-	-	-	-	-	-
2001	-	-	-	-	133.793	(20.858)	-	-
2002	106.253	(15.813)	-	-	-	-	-	-
2003	75.960	(13.314)	-	-	**82.928**	(9.010)	128.450	(20.062)
2004	**205.939**	(33.216)	-	-	**106.119**	(15.596)	**99.902**	(12.027)
2005	**70.983**	(13.845)	-	-	-	-	**76.932**	(5.965)
2006	88.420	(22.851)	-	-	99.867	(9.803)	130.900	(14.816)
2007	**82.040**	(11.491)	-	-	**74.615**	(7.383)	**70.940**	(5.615)
2008	**50.877**	(5.355)	-	-	**94.232**	(11.456)	**108.195**	(9.978)
2009	**175.289**	(39.920)	-	-	-	-	**124.004**	(11.808)
2010	163.545	(34.444)	-	-	-	-	184.960	(37.720)
2011	**89.392**	(23.218)	-	-	-	-	**117.222**	(11.857)
2012	**92.588**	(11.926)	-	-	-	-	-	-
2013	-	-	-	-	-	-	-	-

Table 3.4: Years for which **survey** length frequencies are available for use in the RC are shown by ✓. * indicates that they are available disaggregated by sex (Rademeyer and Butterworth 2014d)

	West Coast		South Coast	
Year	Summer	Winter	Spring	Autumn
1985	✓	✓	-	-
1986	✓	✓	✓	-
1987	✓	✓	✓	-
1988	✓	✓	-	✓
1989	-	✓	-	-
1990	✓	✓	-	-
1991	✓	-	-	-
1992	✓	-	-	✓
1993	✓*	-	-	✓*
1994	✓*	-	-	✓*
1995	✓*	-	-	✓*
1996	✓*	-	-	✓*
1997	✓*	-	-	✓*
1998	-	-	-	-
1999	✓*	-	-	✓
2000	-	-	-	-
2001	-	-	✓	-
2002	✓	-	-	-
2003	✓	-	✓	✓
2004	✓	-	✓	✓
2005	✓	-	-	✓
2006	✓*	-	✓*	✓*
2007	✓*	-	✓*	✓*
2008	✓*	-	✓*	✓*
2009	✓*	-	-	✓*
2010	✓*	-	-	✓*
2011	✓*	-	-	✓*
2012	✓*	-	-	✓*
2013	-	-	-	-

Table 3.5: Years for which **commercial** length frequencies are available for use in the RC are shown by ✓. * indicates that they are are available disaggregated by sex (Somhlaba and Leslie 2014).

Year	Offshore trawl		Inshore trawl	Longline				
	Species combined		*M. cap*	Spp combined	*M. para*	*M. cap*	*M. para*	*M. cap*
	WC	SC	SC		WC		SC	
1975	-	✓	-	-	-	-	-	-
1976	-	✓	-	-	-	-	-	-
1977	-	✓	-	-	-	-	-	-
1978	-	✓	-	-	-	-	-	-
1979	-	✓	-	-	-	-	-	-
1980	-	✓	-	-	-	-	-	-
1981	✓	✓	✓	-	-	-	-	-
1982	✓	✓	✓	-	-	-	-	-
1983	✓	✓	✓	-	-	-	-	-
1984	✓	✓	✓	-	-	-	-	-
1985	✓	✓	✓	-	-	-	-	-
1986	✓	✓	✓	-	-	-	-	-
1987	✓	✓	✓	-	-	-	-	-
1988	✓	✓	✓	-	-	-	-	-
1989	✓	✓	✓	-	-	-	-	-
1990	✓	✓	✓	-	-	-	-	-
1991	✓	✓	✓	-	-	-	-	-
1992	✓	✓	✓	-	-	-	-	-
1993	✓	✓	✓	-	-	-	-	-
1994	✓	✓	✓	✓	-	-	-	✓
1995	✓	✓	✓	✓	-	-	-	✓
1996	✓	✓	✓	✓	-	-	-	✓
1997	✓	-	-	✓	-	-	-	✓
1998	✓	-	✓	-	-	-	-	-
1999	✓	-	✓	-	-	-	-	-
2000	-	-	✓	-	✓*	✓*	-	✓*
2001	-	-	✓	-	✓*	✓*	✓*	✓*
2002	-	-	-	-	✓*	✓*	-	✓*
2003	-	-	-	-	✓*	✓*	-	✓*
2004	-	-	-	-	✓*	✓*	-	✓*
2005	✓	-	-	-	✓*	✓*	-	✓*
2006	✓	-	-	-	✓*	✓*	✓*	✓*
2007	✓	-	✓	-	✓*	✓*	-	
2008	✓	-	✓	-	✓*	✓*	✓*	✓*
2009	✓	-	✓	-	✓*	✓*	✓*	✓*
2010	✓	-	✓	-	✓*	✓*	✓*	✓*
2011	✓	-	✓	-	-	-	-	-
2012	✓	-	✓	-	-	-	-	-

Table 3.6: Final four CMPs considered in the process of selecting OMP-2014 for hake (Rademeyer and Butterworth 2014b).

	135 000t av. annual catch	138 000t av. annual catch
2015 and 2016 TACs not fixed	$CMPfinal1_{135}$	$CMPfinal1_{138}$
2015 and 2016 TACs fixed at 147 500t	$CMPfinal2_{135}$	$CMPfinal2_{138}$

Table 3.7: Median and 90% PIs for a series of performance statistics under the final CMP - selected as OMP-2014 $CMPfinal2_{135}$ (Rademeyer and Butterworth 2014b). BS indicates that the statistic shown applies to both species, values in bold are prespecified, and * indicates that the units are thousand tonnes.

$C_{2014} - C_{2017}$ are the TACs in the respective years.

$B_y^{sp}/MSYL$ is the female spawning biomass in year y (2014-2017) relative to the maximum sustainable yield level.

avC: 2015-2024 is the medium term average TAC over the period.

C_{low}: 2015-2034 is the lowest expected TAC during the projection period.

AAV: 2015-2034 is the average annual variation in TAC expressed as a proportion.

B_{low}^{sp}/B_y^{sp} is the lowest expected female spawning biomass during the projection period, relative to year y level.

$B_y^{sp}/MSYL$ is the expected female spawning biomass in year y, relative to the maximum sustainable yield level.

$CPUE_{2024}/CPUE_{2013}$ and E_{2024}/E_{2013} are measures of catch per unit effort and effort respectively in 2024 relative to the 2013 level.

$Prob\ decl > 20\%(2015-2017)$ and $Prob\ decl > 20\%(2016-2018)$ are the probability of a decline in the TAC greater than 20% over the 2015-2017 and 2016-2018 periods respectively.

$Prob\ decl > 20\%(2015-2032)$ is the probability of a decline in the TAC greater than 20% over any consecutive three years for such periods commencing 2015-2032.

More details concerning these performance statistics may be found in Rademeyer (2014a).

Quantity		Median	(90% PI)	Quantity		Median	(90% PI)
C_{2014}		**155.3***		$B_{low}^{sp}/B_{2014}^{sp}$	cap	1.02	(0.79; 1.10)
C_{2015}	BS	**147.5***		$B_{low}^{sp}/B_{2007}^{sp}$	para	1.32	(0.85; 1.63)
C_{2016}	BS	**147.5***		$B_{low}^{sp}/B_{2007}^{sp}$	cap	1.68	(1.34; 1.88)
C_{2017}	BS	140.1*	(140.1; 146.0)	$B_{2024}^{sp}/MSYL$	para	1.06	(0.64; 1.96)
$B_{2014}^{sp}/MSYL$	para	0.83	(0.63; 1.26)	$B_{2024}^{sp}/MSYL$	cap	3.40	(1.82; 4.82)
$B_{2015}^{sp}/MSYL$	para	0.74	(0.60; 1.05)	$B_{2034}^{sp}/MSYL$	para	1.19	(0.74; 2.35)
$B_{2016}^{sp}/MSYL$	para	0.68	(0.55; 1.00)	$CPUE_{2024}/CPUE_{2013}$	BS	1.11	(0.94; 1.34)
$B_{2017}^{sp}/MSYL$	para	0.66	(0.51; 1.06)	E_{2024}/E_{2013}	BS	0.76	(0.60; 0.94)
avC: 2015-2024	BS	**135.0***	(122.2; 146.5)	$Prob\ decl > 20\%(2015-2017)$		0.01	
C_{low} : 2015 – 2034	BS	115.5*	(94.5; 133.1)	$Prob\ decl > 20\%(2016-2018)$		0.02	
AAV: 2015-2034	BS	0.04	(0.02; 0.06)	$Prob\ decl > 20\%(2015-2032)$		0.00	(0.00; 0.00)
$B_{low}^{sp}/B_{2014}^{sp}$	para	0.80	(0.53; 0.99)				

Table 3.8: Tuning parameter values for OMP-2014 (Rademeyer 2014b) - see Equations 3.3.2 and 3.3.7.

	M. paradoxus	*M. capensis*
J_0	0.132	0.240
b	83.83	33.33
$J^{thresh1}$	0.75	
$J^{thresh2}$	0.65	
x	25	

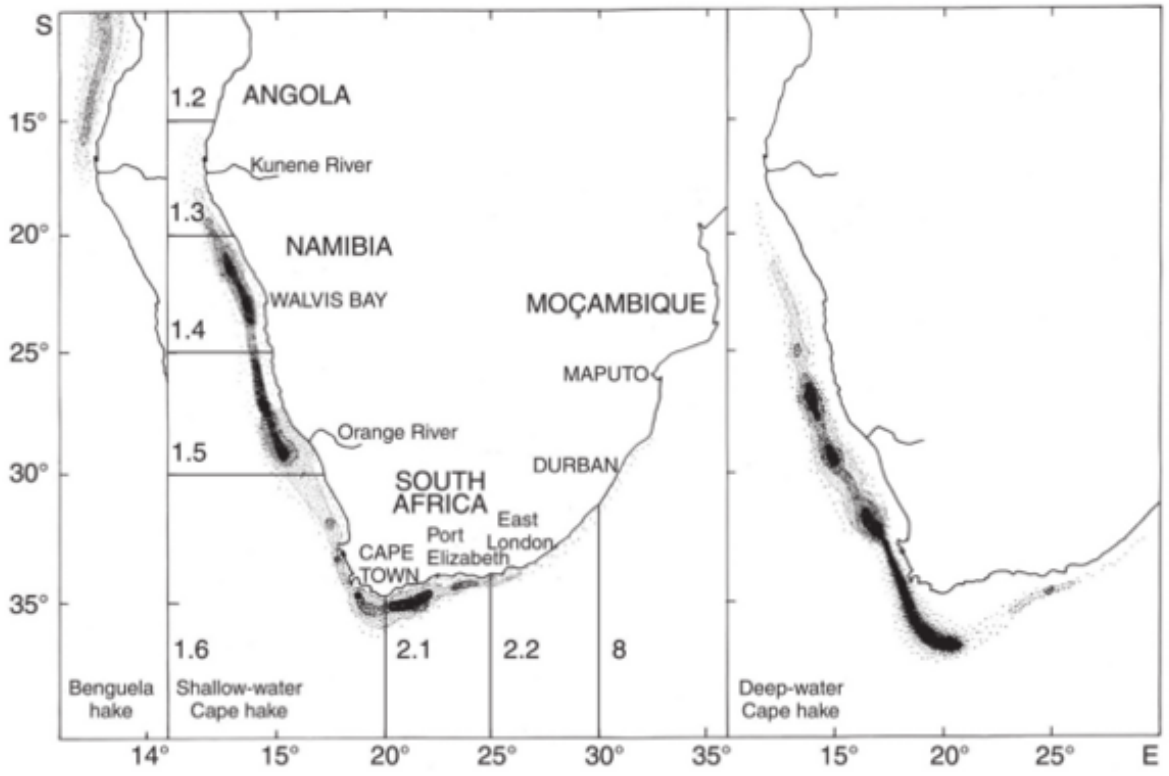

Figure 3.1: ICSEAF management units and species distribution for southern African hake: Benguela hake (*M. polli*), shallow-water Cape hake (*M. capensis*) and deep-water Cape Hake (*M. paradoxus*) (the map has been reproduced from Payne (1989) with permission).

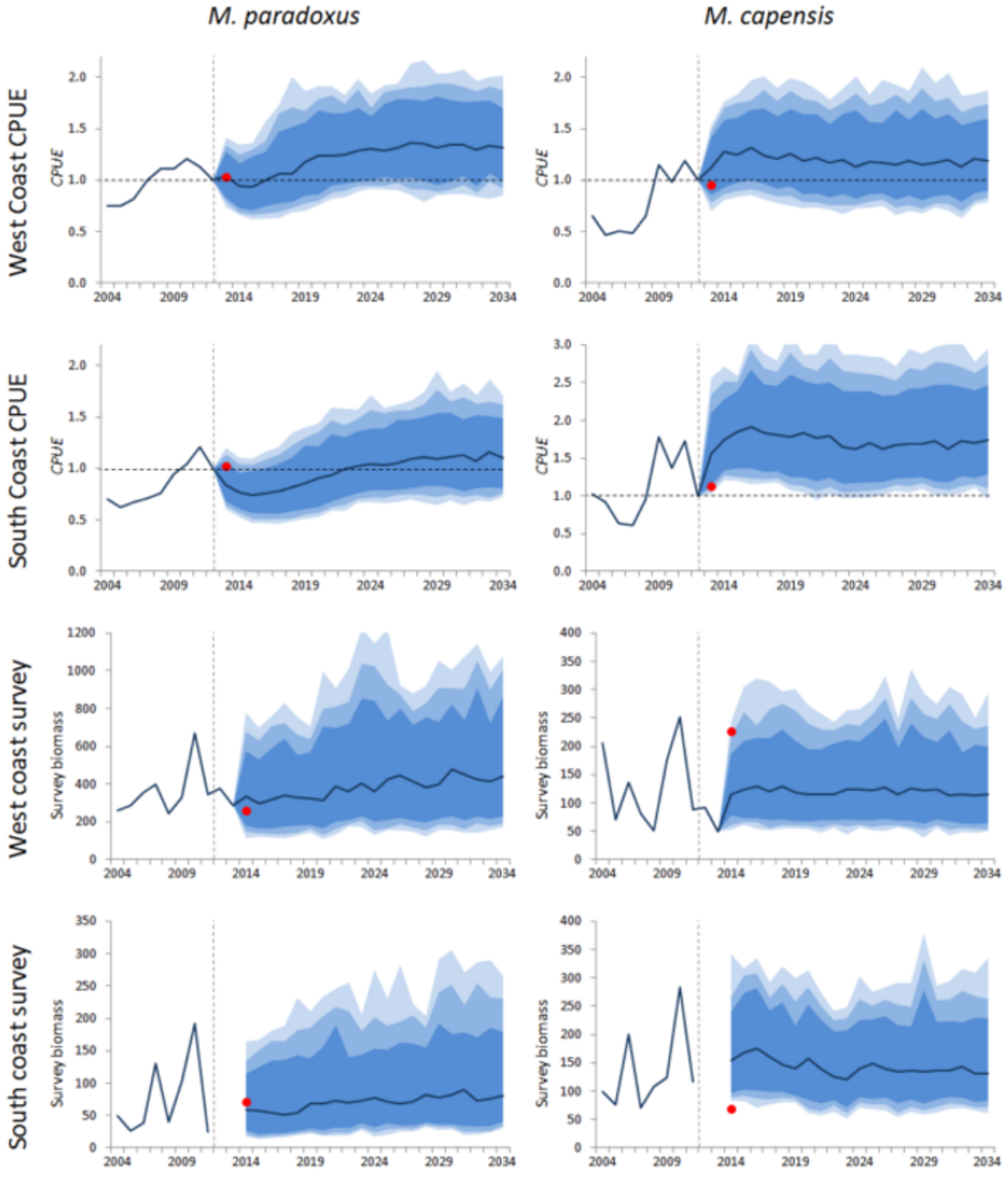

Figure 3.2: Projections (95%, 90% and 80% PI and medians) for the (combined) RS under OMP-2014 together with the resource abundance index data for the first year for which these data were not available at the time the RS OMs were conditioned. The red dots show these most recent data points (Rademeyer 2014b).

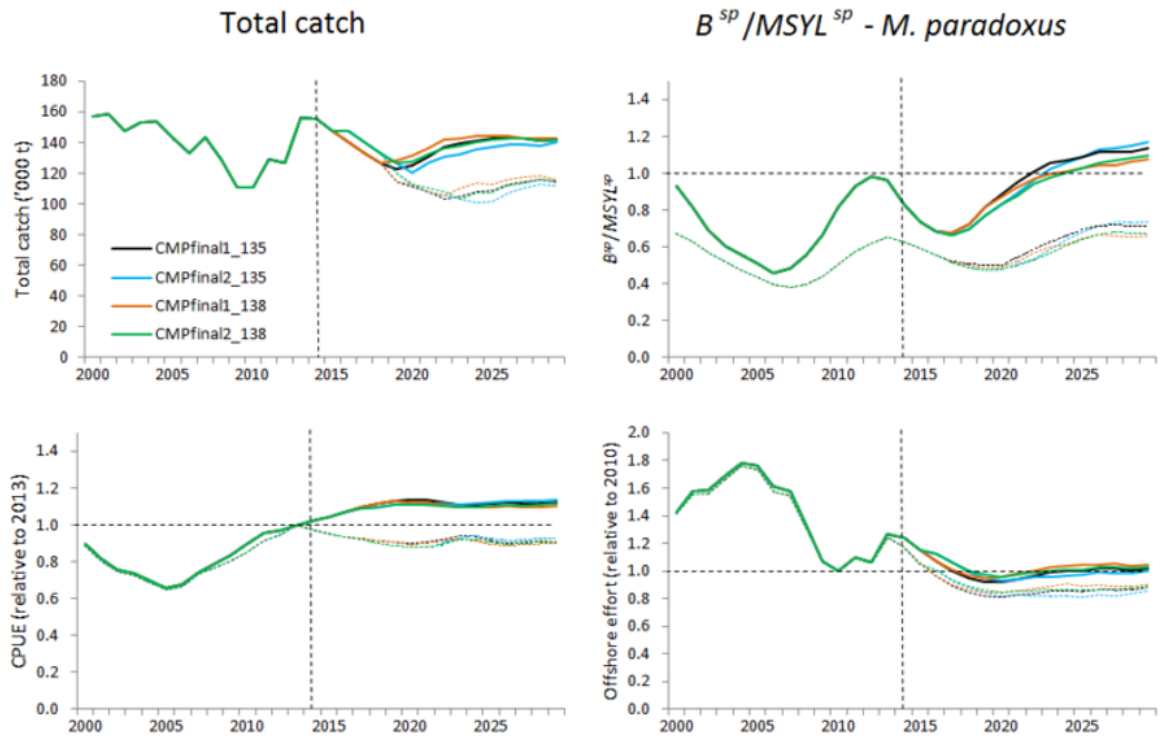

Figure 3.3: Medians (full lines) and lower 5%iles (dotted lines) for total catch (top row, LHS), *M. paradoxus* spawning biomass (relative to MSYL level - top row, RHS), CPUE (relative to 2013, bottom row, LHS) and effort (relative to 2010, bottom row, RHS) for the RS under the final four CMPs (Rademeyer and Butterworth 2014b).

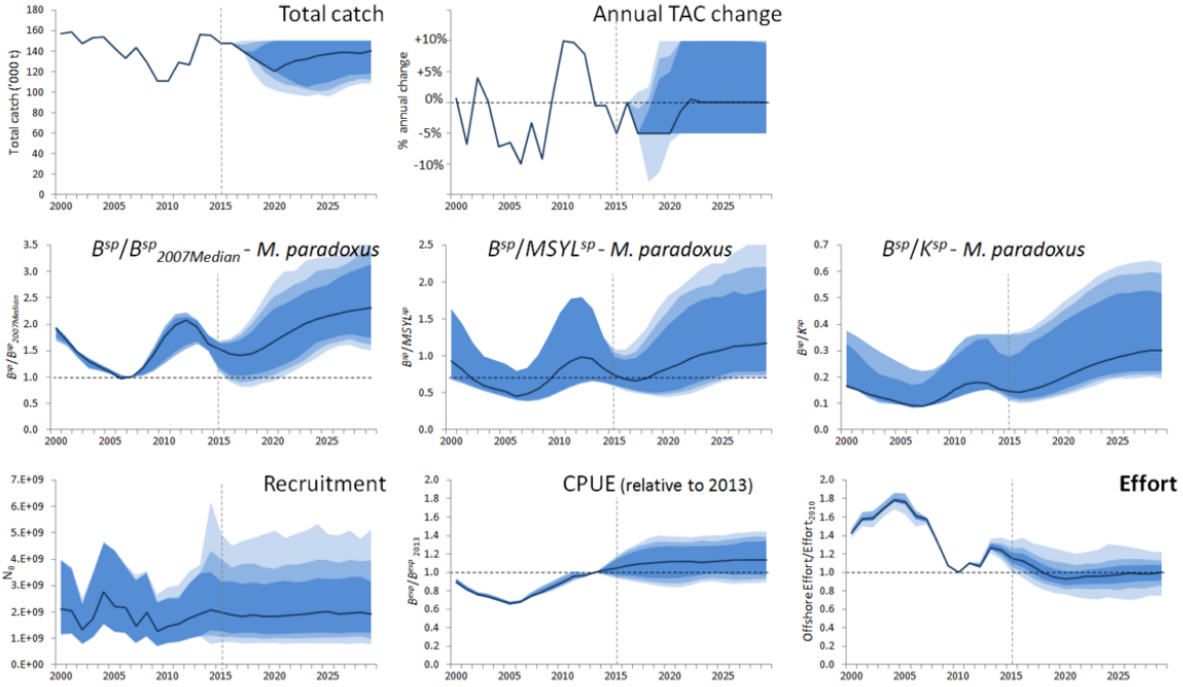

Figure 3.4: 95, 90 and 80% PI and median for a series of performance statistics for the CMP selected for OMP-2014, $CMPfinal2_{135}$, under the RS (Rademeyer and Butterworth 2014b).

Appendices

3.A South African hake 2014 Reference Case assessment model

This text is copied directly from Rademeyer and Butterworth (2014d). The addendum following contains cross-references from the main text of Rademeyer and Butterworth (2014d).

The model used is a gender-disaggregated Statistical Catch-at-Age (SCAA), which is fitted directly to age-length keys (ALKs) and length frequencies. The model also assesses the two species as two independent stocks and is fitted to species-disaggregated data as well as species-combined data. A distinction is made between the west and the south coasts (see Figure 3.A.2), with hake movement surrogated using the "areas-as-fleets" approach. "Fleet" below therefore refer to a combination of gear type (offshore trawl, inshore trawl, longline and handline) and area (west and south coasts). The general specifications and equations of the overall model are set out below, together with some key choices in the implementation of the methodology. Details of the contributions to the log-likelihood function from the different data considered are also given. Quasi-Newton minimisation is used to minimise the total negative log-likelihood function (implemented using AD Model Builder™, Otter Research, Ltd. (Fournier *et al*. 2011)).

3.A.1 Population Dynamics

3.A.1.1 Numbers-at-age

The resource dynamics of the two populations (*M. capensis* and *M. paradoxus*) of the South African hake are modelled by the following set of equations.

Note: for ease of reading, the 'species' subscript *s* has been omitted below where equations are identical for the two species and in the interests of less cumbersome notation, subscripts have been separated by commas only when this is necessary for clarity.

$$N^{g}_{y+1,0} = R^{g}_{y+1} \tag{3.A.1}$$

$$N^{g}_{y+1,a+1} = \left(N^{g}_{ya} e^{-M^{g}_{a}/2} - \sum_{f} C^{g}_{fya} \right) e^{-M^{g}_{a}/2} \qquad \text{for } 0 \le a \le m-2 \tag{3.A.2}$$

$$\begin{aligned} N^{g}_{y+1,m} = & \left(N^{g}_{y,m-1} e^{-M^{g}_{m-1}/2} - \sum_{f} C^{g}_{f,y,m-1} \right) e^{-M^{g}_{m-1}/2} \\ & + \left(N^{g}_{ym} e^{-M^{g}_{m}/2} - \sum_{f} C^{g}_{fym} \right) e^{-M^{g}_{m}/2} \end{aligned} \tag{3.A.3}$$

where

N^{g}_{ya} is the number of fish of gender *g* and age *a* at the start of year *y*;

R^{g}_{y} is the recruitment (number of 0-year-old fish) of fish of gender *g* at the start of year *y*;

m is the maximum age considered (taken to be a plus-group);

M^{g}_{a} denotes the natural mortality rate on fish of gender *g* and age *a*; and

C^{g}_{fya} is the number of hake of gender *g* and age *a* caught in year *y* by fleet *f*.

3.A.1.2 Recruitment

The number of recruits (i.e. new zero-year old fish) at the start of year *y* is assumed to be related to the corresponding female spawning stock size (i.e., the biomass of mature female fish). The underlying assumptions are that female spawning output can limit subsequent recruitment, but that there are always sufficient males to provide adequate fertilisation. The recruitment and corresponding female spawning stock size are related by means of the Beverton-Holt (Beverton and Holt 1957) or a modified (generalised) form of the Ricker stock-recruitment relationship. These forms are parameterized in terms of the "steepness" of the stock-recruitment relationship, *h*, the pre-exploitation equilibrium female spawning biomass, $K^{♀,sp}$, and the pre-exploitation recruitment, R_0 and assuming a 50:50 sex-split at recruitment:

$$R_y^g = \frac{4hR_0 B_y^{♀,sp}}{K^{♀,sp}(1-h)+(5h-1)B_y^{♀,sp}} e^{(\varsigma_y - \sigma_R^2/2)} \qquad \text{(3.A.4a)}$$

for the Beverton-Holt stock-recruitment relationship and

$$R_y^g = \alpha B_y^{♀,sp} \exp\left(-\beta\left(B_y^{♀,sp}\right)^\gamma\right) e^{(\varsigma_y - \sigma_R^2/2)} \qquad \text{(3.A.4b)}$$

with

$$\alpha = R_0 \exp\left(\beta\left(K^{♀,sp}\right)^\gamma\right) \qquad \text{and} \qquad \beta = \frac{\ln(5h)}{\left(K^{♀,sp}\right)^\gamma\left(1-5^{-\gamma}\right)}$$

for the modified Ricker relationship (for the true Ricker, γ=1) where

ς_y reflects fluctuation about the expected recruitment in year *y*;

σ_R is the standard deviation of the log-residuals, which is input ($\sigma_R = 0.45$ and is taken to decrease linearly from this value to 0.1 over the last five years to statistically stabilise estimates of recent recruitment).

$B_y^{♀,sp}$ is the female spawning biomass at the start of year *y*, computed as:

$$B_y^{♀,sp} = \sum_{a=1}^{m} f_a^{♀} w_a^{♀} N_{ya}^{♀} \qquad \text{(3.A.5)}$$

where

w_a^g is the begin-year mass of fish of gender *g* and age *a*;

f_a^g is the proportion of fish of gender *g* and age *a* that are mature (converted from maturity-at-length, see equation 3.A.47); and

$$R_0 = K^{♀,sp} / \left[\sum_{a=1}^{m-1} f_a^{♀} w_a^{♀} e^{-\sum_{a'=0}^{a-1} M_{a'}^g} + f_m^{♀} w_m^{♀} \frac{e^{-\sum_{a'=0}^{m-1} M_{a'}^g}}{1-e^{-M_m^g}}\right] \qquad \text{(3.A.6)}$$

For the Beverton-Holt form, *h* is bounded above by 0.98 to preclude high recruitment at extremely low spawning biomass, whereas for the modified Ricker form, *h* is bounded above by 1.5 to preclude extreme compensatory behaviour. The Reference Case uses the modified Ricker form to model recruitment.

3.A.1.3 Total catch and catches-at-age

The fleet-disaggregated catch by mass, in year *y* is given by:

$$C_{fy} = \sum_{g}\sum_{a=0}^{m} \tilde{w}^{g}_{fy,a+1/2}\, C^{g}_{fya} = \sum_{g}\sum_{a=0}^{m} \tilde{w}^{g}_{fy,a+1/2}\, N^{g}_{ya} e^{-M^{g}_{a}/2} F_{fy} S^{g}_{fya} \qquad (3.A.7)$$

where

C^{g}_{fya} is the catch-at-age, i.e. the number of fish of gender *g* and age *a*, caught in year *y* by fleet *f*;

F_{fy} is the fishing mortality of a fully selected age class, for fleet *f* in year *y* (independent of *g*);

$$S^{g}_{fya} = \sum_{l} S^{g}_{fyl} P^{g}_{a+1/2,l} \qquad (3.A.8)$$

S^{g}_{fya} is the commercial selectivity of gender *g* at age *a* for fleet *f* and year *y*;

S^{g}_{fyl} is the commercial selectivity of gender *g* at length *l* for year *y*, and fleet *f;*

$$\tilde{w}^{g}_{fy,a+1/2} = \sum_{l} S^{g}_{fyl} w^{g}_{l} P^{g}_{a+1/2,l} \Big/ \sum_{l} S^{g}_{fyl} P^{g}_{a+1/2,l} \qquad (3.A.9)$$

$\tilde{w}^{g}_{fy,a+1/2}$ is the selectivity-weighted mid-year weight-at-age *a* of gender *g* for fleet *f* and year *y*;

w^{g}_{l} is the weight of fish of gender *g* and length *l*;

$P^{g}_{a+1/2,l}$ is the mid-year proportion of fish of age *a* and gender *g* that fall in the length group *l* (i.e., $\sum_{l} P^{g}_{a+1/2,l} = 1$ for all ages *a*).

The matrix *P* is calculated under the assumption that length-at-age is log-normally distributed about a mean given by the von Bertalanffy equation, i.e.:

$$\ln l_{a} \sim N\left[\ln\left(l_{\infty}\left(1-e^{-\kappa(a-t_{0})}\right)\right); \left(\frac{\theta_{a}}{l_{\infty}\left(1-e^{-\kappa(a-t_{0})}\right)}\right)^{2} \right] \qquad (3.A.10)$$

where θ_{a} is the standard deviation of length-at-age *a*, which is estimated directly in the model fitting for age 0, and for ages 1 and above a linear relationship applies:

$$\theta_{a} = \begin{cases} B_{0} & \text{for } a = 0 \\ (\beta a + \alpha) & \text{for } 1 \le a \le m \end{cases}$$

with species and gender-specific B_0, α and β estimated in the model fitting procedure. A penalty is added to ensure that θ_{a} is increasing with age, i.e. β>0.

3.A.1.4 Exploitable and survey biomasses

The model estimate of the mid-year exploitable ("available") component of biomass for each species and fleet is calculated by converting the numbers-at-age into mid-year mass-at-age and applying natural and fishing mortality for half the year:

$$B^{ex}_{fy} = \sum_{g}\sum_{a=0}^{m} \tilde{w}^{g}_{fy,a+1/2} S^{g}_{fya} N^{g}_{ya} e^{-M^{g}_{a}/2} \left(1 - \sum_{f} S^{g}_{fya} F_{fy} \Big/ 2\right) \qquad (3.A.11)$$

The model estimate of the survey biomass at the start of the year (summer) is given by:

$$B_y^{surv} = \sum_g \sum_{a=0}^{m_s} \tilde{w}_a^{g,sum} S_a^{g,sum} N_{ya}^g \tag{3.A.12}$$

and in mid-year (winter):

$$B_y^{surv} = \sum_g \sum_{a=0}^{m} \tilde{w}_{a+1/2}^{g,win} S_a^{g,win} N_{ya}^g e^{-M_a^g/2} \left(1 - \sum_f S_{fya}^g F_{fy} \Big/ 2\right) \tag{3.A.13}$$

where

$S_a^{g,sum/win}$ is the survey selectivity of gender *g* for age *a,* converted from survey selectivity-at-length in the same manner as for the commercial selectivity (eqn 3.A.8);

$\tilde{w}_a^{g,i}$ is the survey selectivity-weighted weight-at-age *a* of gender *g* for survey *i*, computed in the same manner as for the commercial selectivity-weight-at-age (equation 3.A.9) and taking account of the begin-year ($\tilde{w}_{y,a}^{g,sum}$ from $P_{a,l}^g$) or mid-year ($\tilde{w}_{y,a+1/2}^{g,win}$ from $P_{a+1/2,l}^g$) nature of the surveys.

Note that both the spring and autumn surveys are taken to correspond to winter (mid-year), and that as with the commercial catch the areas-as-fleets approach underlies the use of selectivity to reflect differences between the west and south coast surveys.

It is assumed that the resource is at the deterministic equilibrium that corresponds to an absence of harvesting at the start of the initial year considered, i.e., $B_1^{g,sp} = K^{g,sp}$, and the year *y*=1 corresponds to 1917 when catches commence.

3.A.2 MSY and related quantities

The equilibrium catch for a fully selected fishing proportion *F** is calculated as:

$$C(F^*) = \sum_g \sum_a \tilde{w}_{a+1/2}^g S_a^g F^* N_a^g(F^*) e^{-\left(\left(M_a^g + S_a^g F^*\right)/2\right)} \tag{3.A.14}$$

where

S_a^g is the average selectivity across all fleets, for the most recent five years;

$$S_a^g = \frac{\sum_{y=2005}^{2009} \sum_f S_{fya}^g F_{fy}}{\max\left(\sum_{y=2005}^{2009} \sum_f S_{fya}^g F_{fy}\right)} \tag{3.A.15}$$

where the maximum is taken over genders and ages; and with

$$N_a^g(F^*) = \begin{cases} R_1(F^*) & \text{for } a = 1 \\ N_{a-1}^g(F^*) e^{-M_{a-1}^g}\left(1 - S_{a-1}^g F^*\right) & \text{for } 1 < a < m \\ \dfrac{N_{m-1}^g(F^*) e^{-M_{m-1}^g}\left(1 - S_{m-1}^g F^*\right)}{\left(1 - e^{-M_m^g}\left(1 - S_m^g F^*\right)\right)} & \text{for } a = m \end{cases} \tag{3.A.16}$$

where

$$R_1\left(F^*\right)=\frac{\alpha B^{♀,sp}\left(F^*\right)}{\beta+B^{♀,sp}\left(F^*\right)} \tag{3.A.17}$$

for a Beverton-Holt stock–recruitment relationship.

The maximum of $C\left(F^*\right)$ is then found by searching over *F** to give F^*_{MSY} , with the associated female spawning biomass given by:

$$B^{♀,sp}_{MSY}=\sum_a f^{♀}_a w^{♀}_a N^{♀}_a\left(F^*_{\mathrm{MSY}}\right) \tag{3.A.18}$$

3.A.3 The likelihood function

The model is fit to CPUE and survey biomass indices, commercial and survey length frequencies, survey age-length keys, as well as to the stock-recruitment curve to estimate model parameters. Contributions by each of these to the negative of the log-likelihood (- $\ell \mathrm{n} L$) are as follows[4].

3.A.3.1 CPUE relative biomass data

The likelihood is calculated by assuming that the observed biomass index (here CPUE) is log-normally distributed about its expected value:

$$I^i_y=\hat{I}^i_y e^{\varepsilon^i_y} \quad \text{or} \quad \varepsilon^i_y=\ell\mathrm{n}\left(I^i_y\right)-\ell\mathrm{n}\left(\hat{I}^i_y\right) \tag{3.A.19}$$

where

I^i_y is the biomass index for year *y* and series *i* (which corresponds to a specified species and fleet);

$\hat{I}^i_y=\hat{q}^i\hat{B}^{ex}_{fy}$ is the corresponding model estimate, where $\hat{B}^{ex}_{fy}$ is the model estimate of exploitable resource biomass, given by equation 3.A.11;

$\hat{q}^i$ is the constant of proportionality for biomass series *i*; and

ε^i_y from $N\left(0,\left(\sigma^i_y\right)^2\right)$.

In cases where the CPUE series are based upon species-aggregated catches (as available pre-1978), the corresponding model estimate is derived by assuming two types of fishing zones: z1) an "*M. capensis* only zone", corresponding to shallow-water and z2) a "mixed zone" (see diagrammatic representation in Figure 3.A.1).

The total catch of hake of both species (*BS*) by fleet *f* in year *y* ($C_{BS,fy}$) can be written as:

$$C_{BS,fy}=C^{z1}_{C,fy}+C^{z2}_{C,fy}+C_{P,fy} \tag{3.A.20}$$

where

$C^{z1}_{C,fy}$ is the *M. capensis* catch by fleet *f* in year *y* in the *M. capensis* only zone (z1);

$C^{z2}_{C,fy}$ is the *M. capensis* catch by fleet *f* in year *y* in the mixed zone (z2); and

$C_{P,fy}$ is the *M. paradoxus* catch by fleet *f* in year *y* in the mixed zone.

[4] Strictly it is a penalised log-likelihood which is maximised in the fitting process, as some contributions that would correspond to priors in a Bayesian estimation process are added.

Catch rate is assumed to be proportional to exploitable biomass. Furthermore, let γ be the proportion of the *M. capensis* exploitable biomass in the mixed zone ($\gamma = B^{ex,z2}_{C,fy} \big/ B^{ex}_{C,fy}$) (assumed to be constant throughout the period for simplicity) and ψ_{fy} be the proportion of the effort of fleet *f* in the mixed zone in year *y* ($\psi_{fy} = E^{z2}_{fy} \big/ E_{fy}$), so that:

$$C^{z1}_{C,fy} = q^{i,z1}_{C} B^{ex,z1}_{Cfy} E^{z1}_{fy} = q^{i,z1}_{C}(1-\gamma) B^{ex}_{C,fy}(1-\psi_{fy}) E_{fy} \quad (3.A.21)$$

$$C^{z2}_{C,fy} = q^{i,z2}_{C} B^{ex,z2}_{C,fy} E^{z2}_{fy} = q^{i,z2}_{C} \gamma B^{ex}_{C,fy} \psi_{fy} E_{fy} \quad \text{and} \quad (3.A.22)$$

$$C_{P,fy} = q^{i}_{P} B^{ex}_{P,fy} E^{z2}_{fy} = q^{i}_{P} B^{ex}_{P,fy} \psi_{fy} E_{fy} \quad (3.A.23)$$

where

$E_{fy} = E^{z1}_{fy} + E^{z2}_{fy}$ is the total effort of fleet *f*, corresponding to combined-species CPUE series *i* which consists of the effort in the *M. capensis* only zone (E^{z1}_{fy}) and the effort in the mixed zone (E^{z2}_{fy});

$q^{i,zj}_{C}$ is the catchability for *M. capensis* (*C*) for biomass series *i*, and zone *zj*; and

q^{i}_{P} is the catchability for *M. paradoxus* (*P*) for biomass series *i*.

It follows that:

$$C_{C,fy} = B^{ex}_{C,fy} E_{fy} \left[q^{i,z1}_{C}(1-\gamma)(1-\psi_{fy}) + q^{i,z2}_{C} \gamma \psi_{fy} \right] \quad (3.A.24)$$

$$C_{P,fy} = B^{ex}_{P,fy} E_{fy} q^{i}_{P} \psi_{fy} \quad (3.A.25)$$

From solving equations 3.A.24 and 3.A.25:

$$s_{fy} = \frac{q^{i,z1}_{C}(1-\gamma)}{\left\{ \frac{C_{C,fy} B^{ex}_{P,fy} q^{i}_{P}}{B^{ex}_{C,fy} C_{P,fy}} - q^{i,z2}_{C}\gamma + q^{i,z1}_{C}(1-\gamma) \right\}} \quad (3.A.26)$$

and:

$$\hat{I}^{i}_{y} = \frac{C_{fy}}{E_{fy}} = \frac{C_{fy} B^{ex}_{P,fy} q^{i}_{P} \psi_{fy}}{C_{P,fy}} \quad (3.A.27)$$

Zone 1 (z1): *M. capensis* only	Zone 2 (z2): Mixed zone
M. capensis: biomass (B^{z1}_{C}), catch(C^{z1}_{C})	*M. capensis*: biomass (B^{z2}_{C}), catch(C^{z2}_{C}) *M. paradoxus*: biomass (B_P), catch(C_P)
Effort in zone 1 (E^{z1})	Effort in zone 2 (E^{z2})

Figure 3.A.1: Diagrammatic representation of the two conceptual fishing zones.

Two species-aggregated CPUE indices are available: the ICSEAF West Coast and the ICSEAF South Coast series. For consistency, *q*'s for each species (and zone) are forced to be in the same proportion:

$$q_s^{SC} = rq_s^{WC} \tag{3.A.28}$$

To correct for possible negative bias in estimates of variance $\left(\sigma_y^i\right)$ and to avoid according unrealistically high precision (and so giving inappropriately high weight) to the CPUE data, lower bounds on the standard deviations of the residuals for the logarithm of the CPUE series have been enforced: for the historic ICSEAF CPUE series (separate West Coast and South Coast series) the lower bound is set to 0.25, and to 0.15 for the recent GLM-standardised CPUE series, i.e.: $\sigma^{ICSEAF} \geq 0.25$ and $\sigma^{GLM} \geq 0.15$.

The contribution of the CPUE data to the negative of the log-likelihood function (after removal of constants) is then given by:

$$-\ell \mathrm{n} L^{CPUE} = \sum_i \sum_y \left[\ell \mathrm{n}\left(\sigma_y^i\right) + \left(\varepsilon_y^i\right)^2 / 2\left(\sigma_y^i\right)^2 \right] \tag{3.A.29}$$

where

σ_y^i is the standard deviation of the residuals for the logarithms of index *i* in year *y*.

Homoscedasticity of residuals for CPUE series is customarily assumed[5], so that $\sigma_y^i = \sigma^i$ is estimated in the fitting procedure by its maximum likelihood value:

$$\hat{\sigma}^i = \sqrt{1/n_i \sum_y \left(\ell \mathrm{n}(I_y^i) - \ell \mathrm{n}(\hat{I}_y^i)\right)^2} \tag{3.A.30}$$

where n_i is the number of data points for biomass index *i*.

In the case of the species-disaggregated CPUE series, the catchability coefficient q^i for biomass index *i* is estimated by its maximum likelihood value, which in the more general case of heteroscedastic residuals is given by:

$$\ln \hat{q}^i = \frac{\sum_y \left(\ln I_y^i - \ln \hat{B}_{fy}^{ex}\right) / \left(\sigma_y^i\right)^2}{\sum_y 1 / \left(\sigma_y^i\right)^2} \tag{3.A.31}$$

In the case of the species-combined CPUE, $q_C^{WC,z1}$, $q_C^{WC,z2}$, q_P^{WC}, *r* and γ are estimated directly in the fitting procedure.

3.A.3.2 Survey biomass data

Data from the research surveys are treated as relative biomass indices in a similar manner to the species-disaggregated CPUE series above, with survey selectivity function $S_a^{g,sum/win}$ replacing the commercial selectivity S_{fya}^g (see equations 3.A.12 and 3.A.13 above, which also take account of the begin- or mid-year nature of the survey).

An estimate of sampling variance is available for most surveys and the associated σ_y^i is generally taken to be given by the corresponding survey CV. However, these estimates likely fail to include all sources of variability, and unrealistically high precision (low variance and hence high weight) could hence be accorded to these indices. The contribution of the survey data to the negative log-likelihood is of the same form as that of the CPUE biomass data (see equation 3.A.29).

[5] There are insufficient data in any series to enable this to be tested with meaningful power.

The procedure adopted takes into account an additional variance $\left(\sigma_A\right)^2$ which is treated as another estimable parameter in the minimisation process, i.e:

$$-\ell \mathrm{n}\, L^{Survey} = \sum_i \sum_y \left[\ell \mathrm{n}\left(\sqrt{\left(\sigma_y^i\right)^2 + \left(\sigma_A\right)^2} \right) + \left(\varepsilon_y^i\right)^2 / 2\left(\left(\sigma_y^i\right)^2 + \left(\sigma_A\right)^2\right) \right] \qquad (3.A.32)$$

This procedure is carried out enforcing the constraint that $\left(\sigma_A\right)^2$>0, i.e. the overall variance cannot be less than its externally input component.

In June 2003, the trawl gear on the *Africana* was changed and a different value for the multiplicative bias factor *q* is taken to apply to the surveys conducted with the new gear. Calibration experiments have been conducted between the *Africana* with the old gear (hereafter referred to as the "old *Africana*") and the *Nansen*, and between the *Africana* with the new gear ("new *Africana*") and the *Nansen*, in order to provide a basis to relate the multiplicative biases of the *Africana* with the two types of gear (q_{old} and q_{new}).

A recent calibration analysis based on "Model 1" (see Table 1, "Model 1" of Smith *et al*., 2013) provided the following estimates:

$\left(q^{new}/q^{old}\right)^{capensis} = 0.652$ with SE=0.073 and

$\left(q^{new}/q^{old}\right)^{paradoxus} = 0.883$ with SE=0.082.

The following contribution is therefore added as a penalty (or a log prior in a Bayesian context) to the negative log-likelihood in the assessment:

$$-\ell nL^{q-ch} = \left(\ell nq_{new} - \ell nq_{old} - \Delta \ell nq\right)^2 \Big/ 2\sigma^2_{\Delta \ell nq} \qquad (3.A.33)$$

A different length-specific selectivity is estimated for the "old *Africana*" and the "new *Africana*".

The survey's catchability coefficients *q* (for the survey with the old *Africana* gear) are constrained to values below 1 (i.e. it is assumed that the nets do not herd the hake):

$$pen^q = \sum_i \left(q_{old}^i - 1\right)^2 \Big/ 0.02^2 \quad \text{if} \quad q_{old}^i > 1 \qquad (3.A.34)$$

3.A.3.3 Commercial proportions at length

Commercial proportions at length from the offshore trawl fleet cannot be disaggregated by species and gender as the data collected did not distinguish these. The model is therefore fit to the proportions at length as determined for both species and gender combined. The catches made by the inshore trawl fleet are assumed to consist of *M. capensis* only, and species and sex information is available over the 2000-2010 period for the longline fleet.

The catches at length are computed as:

$$C_{fyl} = \sum_s \sum_g \sum_{a=0}^{m} N_{sya}^g F_{sfy} S_{sfyl}^g P_{s,a+1/2,l}^g e^{-M_{sa}^g/2} \left(1 - \sum_f S_{sfya}^g F_{fy} \Big/ 2\right) \qquad (3.A.35)$$

where the summation over species and gender is taken only where appropriate.

The predicted proportions at length:

$$\hat{p}_{yl}^i = C_{fyl} \Big/ \sum_{l'} C_{fyl'} \qquad (3.A.36)$$

The contribution of the proportion at length data to the negative of the log-likelihood function when assuming an "adjusted" lognormal error distribution (Punt and Kennedy, 1997) is given by:

$$-\ell \mathrm{n} L^{\text{length}} = 0.1 \sum_{y} \sum_{l} \left[\ell n\left(\sigma^{i}_{len} / \sqrt{p^{i}_{yl}} \right) + p^{i}_{yl} \left(\ell n p^{i}_{yl} - \ell n\, \hat{p}^{i}_{yl} \right)^2 / 2\left(\sigma^{i}_{len} \right)^2 \right] \quad \text{(3.A.37)}$$

where the superscript '*i*' refers to a particular series of proportions at length data which reflect a specified fleet, species and sex (or combination thereof); and

σ^{i}_{len} is the standard deviation associated with the proportion at length data, which is estimated in the fitting procedure by:

$$\hat{\sigma}^{i}_{len} = \sqrt{\sum_{y} \sum_{l} p^{i}_{yl} \left(\ln\, p^{i}_{yl} - \ln\, \hat{p}^{i}_{yl} \right)^2 / \sum_{y} \sum_{l} 1} \quad \text{(3.A.38)}$$

The initial 0.1 multiplicative factor in equation 3.A.37 is a somewhat arbitrary downweighting to allow for correlation between proportions in adjacent length groups. The coarse basis for this adjustment is the ratio of effective number of age-classes present to the number of length groups in the minimisation, under the argument that independence in variability is likely to be more closely related to the former.

Commercial proportions at length are incorporated in the likelihood function using equation 3.A.37, for which the summation over length *l* is taken from length l_{minus} (considered as a minus group) to l_{plus} (a plus group). The length for the minus- and plus-groups are fleet specific and are chosen so that typically a few percent, but no more, of the fish sampled fall into these two groups.

3.A.3.4 Survey proportions at length

The survey proportions at length are incorporated into the negative of the log-likelihood in an analogous manner to the commercial catches-at-age, assuming an adjusted log-normal error distribution (equation 3.A.37). In this case however, data are disaggregated by species, and for some surveys further disaggregated by gender:

$p^{g,surv}_{syl} = \dfrac{C^{g,surv}_{syl}}{\sum_{g} \sum_{l'} C^{g,surv}_{syl'}}$ is the observed proportion of fish of species *s*, gender *g* and length *l* from survey *surv* in year *y*; and

$\hat{p}^{g,surv}_{syl}$ is the expected proportion of fish of species *s*, gender *g* and length *l* in year *y* in the survey *surv*, given by:

$$\hat{p}^{g,surv}_{syl} = \frac{\sum_{a} S^{g,sum}_{sl} P^{g}_{sal} N^{g}_{sya}}{\sum_{g} \sum_{l'} \sum_{a} S^{g,sum}_{sl'} P^{g}_{sal'} N^{g}_{sya}} \quad \text{(3.A.39)}$$

for begin-year (summer) surveys, or

$$\hat{p}^{g,surv}_{syl} = \frac{\sum_{a} S^{g,win}_{sl} P^{g}_{s,a+1/2,l} N^{g}_{sya} e^{-M^{g}_{sa}/2} \left(1 - \sum_{f} S^{g}_{sfya} F_{sfy} \Big/ 2 \right)}{\sum_{g} \sum_{l'} \sum_{a} S^{g,win}_{sl'} P^{g}_{s,a+1/2,l'} N^{g}_{sya} e^{-M^{g}_{sa}/2} \left(1 - \sum_{f} S^{g}_{sfya} F_{sfy} \Big/ 2 \right)} \quad \text{(3.A.40)}$$

for mid-year (autumn, winter or spring) surveys.

3.A.3.5 Age-length keys

Under the assumption that fish are sampled randomly with respect to age within each length-class, the contribution to the negative log-likelihood for the ALK data (ignoring constants) is:

$$-\ln L^{ALK} = -w\sum_{i}\sum_{l}\sum_{a}\left[A_{i,l,a}^{obs}\ln\left(\hat{A}_{i,l,a}\right) - A_{i,l,a}^{obs}\ln\left(A_{i,l,a}^{obs}\right)\right] \quad (3.A.41)$$

where

w is a downweighting factor to allow for overdispersion in these data compared to the expectation for a multinomial distribution with independent data; this downweighting factor is somewhat arbitrarily set to 0.01 to avoid these data overriding trend information in the indices of biomass;

$A_{i,a,l}^{obs}$ is the observed number of fish of size class *l* that fall in age *a*, for ALK *i* (a specific combination of survey, year, species and gender);

$\hat{A}_{i,a,l}$ is the model estimate of $A_{i,a,l}^{obs}$, computed as:

$$\hat{A}_{i,a,l} = W_{i,l}\frac{C_{i,a,l}\tilde{A}_{a,l}}{\sum_{a'}C_{i,a',l}\tilde{A}_{a',l}} \quad (3.A.42)$$

where

$W_{i,l}$ is the number of fish in length class *l* that were aged for ALK *i*,

$\tilde{A}_{a,l} = \sum_{a}P(a'|a)A_{a,l}$ is the ALK for age *a* and length *l* after accounting for age-reading error,

with $P(a'|a)$, the age-reading error matrix, representing the probability of an animal of true age *a* being aged to be that age or some other age *a'*.

Age-reading error matrices have been computed for each reader and for each species as reported in Appendix A (Rademeyer and Butterworth 2014d).

When multiple readers age the same fish, these data are considered to be independent information in the model fitting.

3.A.3.6 Stock-recruitment function residuals

The stock-recruitment residuals are assumed to be log-normally distributed. Thus, the contribution of the recruitment residuals to the negative of the log-likelihood function is given by:

$$-\ell nL^{SR} = \sum_{s}\left[\sum_{y=y1}^{y2}\varsigma_{sy}{}^{2}\Big/2\sigma_{R}^{2} + \left(\sum_{y=y1}^{y2}\varsigma_{sy}\right)^{2}\Big/0.01^{2}\right] \quad (3.A.43)$$

where

ς_{sy} is the recruitment residual for species *s*, and year *y*, which is assumed to be log-normally distributed with standard deviation σ_R and which is estimated for year *y1* to *y2* (see equation 3.A.4) (estimating the stock-recruitment residuals is made possible by the availability of catch-at-age data, which give some indication of the age-structure of the population); and

σ_R is the standard deviation of the log-residuals, which is input.

The stock-recruitment residuals are estimated for years 1985 to 2013, with recruitment for other years being set deterministically (i.e. exactly as given by the estimated stock-recruitment curve) as there is insufficient catch-at-age information to allow reliable residual estimation for earlier years. A limit on the recent recruitment fluctuations is set

by having the σ_R (which measures the extent of variability in recruitment – see equation 3.A.43) decreasing linearly from 0.45 in 2004 to 0.1 in 2009, thereby effectively forcing recruitment over the last years to lie closer to the stock-recruitment relationship curve.

The second term on the right hand side is introduced to force the average of the residuals estimated over the period from *y1* to *y2* to be close to zero, to assist stabilise the estimation.

3.A.4 Model parameters

3.A.4.1 Estimable parameters

The primary parameters estimated are the species-specific female virgin spawning biomass $\left(K_s^{♀p}\right)$ and "steepness" (h_s) and γ (for the modified Ricker curve used in the Reference Case, see equation 3.A.4b) of the stock-recruitment relationship. The standard deviations σ^i for the CPUE series residuals (the species-combined as well as the GLM-standardised series) as well as the additional variance $\left(\sigma_A^i\right)^2$ for each species are treated as estimable parameters in the minimisation process. Similarly, in the case of the species-combined CPUE, $q_C^{WC,z1}$, $q_C^{WC,z2}$, q_P^{WC}, r and γ are directly estimated in the fitting procedure.

The species- and gender-specific von Bertalanffy growth curve parameters (l_∞, κ and t_0) are estimated directly in the model fitting process, as well as the B_0, α and β, values used to compute the standard deviation of the length-at-age a.

The following parameters are also estimated in the model fits undertaken (if not specifically indicated as fixed):

3.A.4.1.1 Natural mortality:

Natural mortality (M_{sa}^{g}) is assumed to be age-specific and is calculated using the following functional form (the selection of the specific form here is based on convenience and is somewhat arbitrary):

$$M_{sa}^{♀} = \begin{cases} M_{s2}^{♀} & \text{for} \quad a \le 1 \\ \alpha_s^M + \dfrac{\beta_s^M}{a+1} & \text{for} \quad 2 \le a \le 5 \\ M_{s5}^{♀} & \text{for} \quad a > 5 \end{cases} \qquad \text{(3.A.44)}$$

and

$$M_{sa}^{males} = \upsilon^s M_{sa}^{females} \qquad \text{(3.A.45)}$$

M_{s0} and M_{s1} are set equal to M_{s2} ($= \alpha_s^M + \beta_s^M/3$) as there are no data (hake of ages younger than 2 are rare in catch and survey data) which would allow independent estimation of M_{s0} and M_{s1}.

When *M* values are estimated in the fit, a penalty is added to the total –lnL so that $M_{s2} \ge M_{s5}$:

$$pen^M = \sum_s \left(M_{s5} - M_{s2}\right)^2 / 0.01^2 \qquad \text{if } M_{s2} < M_{s5} \qquad \text{(3.A.46)}$$

For the Reference Case, the following values are fixed: $M_{s2}^{♀} = 0.75$ and $M_{s5}^{♀} = 0.375$ for both species and genders.

3.A.4.1.2 Stock-recruitment residuals:

Stock-recruitment residuals ς_{sy} are estimable parameters in the model fitting process. They are estimated separately for each species from 1985 to the present, and set to zero pre-1985 because there are no catch-at-length data for that period to provide the information necessary to inform estimation.

Table 3.A.1 summarises the estimable parameters, excluding the selectivity parameters.

3.A.4.1.3 Survey fishing selectivity-at-length:

The survey selectivities are estimated directly for seven pre-determined lengths for *M. paradoxus* and *M. capensis*. When the model was fitted to proportion-at-age rather than proportion-at-length, survey selectivities were estimated directly for each age (i.e. seven age classes). The lengths at which selectivity is estimated directly are survey specific (at constant intervals between the minus and plus groups) and are given in Table 3.A.2. Between these lengths, selectivity is assumed to change linearly. The slope (trend) from lengths l_{minus}+1 to l_{minus} is assumed to continue exponentially to lower lengths down to length *1*, and similarly the slope from lengths l_{plus}-1 to l_{plus} for *M. paradoxus* and *M. capensis* to continue for greater lengths.

For the South Coast spring and autumn surveys, gender-specific selectivities are estimated for *M. paradoxus*. Furthermore, the female selectivities are scaled down by a parameter estimated for each of these two surveys to allow for the male predominance in the survey catch. This is done for *M. paradoxus* on the South Coast only, as the catch-at-length data for *M. paradoxus* West Coast surveys and *M. capensis* on both coasts do not show substantial gender differences

A penalty is added to the total –lnL to smooth the selectivities to smooth the selectivities by penalising deviations from straight line dependence (the choice of a weighting of 3 was made empirically to balance this term having sufficient but not undue influence):

$$pen^{survS} = \sum_i \sum_{L=L_1+1}^{L_7-1} 3\left(S^i_{L-1} - 2S^i_L + S^i_{L+1}\right)^2 \qquad \text{(3.A.47)}$$

where *i* is a combination of survey, species and gender.

3.A.4.1.4 Commercial fishing selectivity-at-length:

The fishing selectivity-at-length for each species and fleet, S_{sfl}, is estimated in terms of a double normal curve given by:

$$S_{sfl} = \exp\left(-\frac{(l - l\max)^2}{2\sigma^2_{Left}}\right) \quad \text{for } l \le l\max$$

$$S_{sfl} = \exp\left(-\frac{(l - l\max)^2}{2\sigma^2_{Right}}\right) \quad \text{for } l > l\max \qquad \text{(3.A.48)}$$

where σ_{Left}, σ_{Right} and $l_{\max}$ are estimable parameters.

Periods of fixed and changing selectivity have been assumed for the offshore trawl fleet to take account of the change in the selectivity at low ages over time in the commercial catches, likely due to the phasing out of the (illegal) use of net liners to enhance catch rates.

Two selectivity periods are also assumed for the longline fleet.

On the South Coast, for *M. paradoxus*, the female offshore trawl selectivity (only the trawl fleet is assumed to catch *M. paradoxus* on the South Coast) is scaled down by a factor taken as the average of those estimated for the South Coast spring and autumn surveys. Although there is no gender information for the commercial catches, the South Coast spring

and autumn surveys catch a much higher proportion of male *M. paradoxus* than female (ratios of about 7:1 and 3.5:1 for spring and autumn respectively). This is assumed to reflect a difference in distribution of the two genders which would therefore affect the commercial fleet similarly.

Details of the fishing selectivities (including the number of parameters estimated) that are used in the assessment are shown in Table 3.A.3.

3.A.4.2 Input parameters and other choice for application to hake

3.A.4.2.1 Age-at-maturity:

The proportion of fish of species *s*, gender *g* and length *l* that are mature is assumed to follow a logistic curve with the parameter values given in Table 3.A.5:

$$f_{sl}^{g} = \left(1 + e^{-\frac{l - l_{50}^{s,g}}{\Delta^{s,g}}}\right)^{-1} \tag{3.A.49}$$

Maturity-at-length is then converted to maturity-at-age as follows:

$$f_{sa}^{g} = \sum_{l} f_{sl}^{g} P_{a,l}^{g} \tag{3.A.50}$$

3.A.4.2.2 Weight-at-length:

The weight-at-length for each species and gender is calculated from the mass-at-length function, with values of the parameters for this function listed in Table 3.A.6.

3.A.4.2.3 Minus- and plus-groups

Because of a combination of gear selectivity and mortality, a relatively small number of fish in the smallest and largest length classes are caught. In consequence, there can be relatively larger errors (in terms of variance) associated with these data. To reduce this effect, the assessment is conducted with minus- and plus-groups obtained by summing the data over the lengths below and above l_{minus} and l_{plus} respectively. The minus- and plus-group used are given in Table 3.A.4. Furthermore, the proportions at length data (both commercial and survey) are summed into 2cm length classes for the model fitting.

Table 3.A.1: Parameters estimated in the model fitting procedure, excluding selectivity parameters.

	No of parameters	Parameters estimated	Bounds enforced
$K^{♀}$	2	$\ln(K^{♀}_{cap})$ and $\ln(K^{♀}_{para})$	(3.5; 9.0)
h	2	h_{cap} and h_{para}	(0.2; 0.98) for BH, (0.2; 1.5) for modified Ricker
Additional variance	2	$\sigma_{A,cap}$ and $\sigma_{A,para}$	(0; 0.5)
Recruitment residuals	58	$\zeta_{\text{cap,1985-2013}}$ and $\zeta_{para,1985-2013}$	(−5; 5)
σ_{CPUE}	6	1 for each series	ICSEAF: (0.25; 1), GLM (0.15; 1)
ICSEAF CPUE	5	$q_C^{WC,z1}$, $q_C^{WC,z2}$, q_P^{WC}, r and γ_R	q and r : (0,10), and γ_R (0; 1)
θ_a	12	For each species and gender: θ_0, θ_1 and θ_{14}	θ_0: (1; 100), θ_1 and θ_{14} : (1; 100)
Growth	12	For each species and gender: L_5, κ and t_0	L_5: (30; 60) κ: (0.00005; 0.2) and t_0: (-10; 0)

Table 3.A.2: Lengths (in cm) at which survey selectivity is estimated directly.

M. paradoxus	West coast summer	13	18	23	28	32	37	42	47
	West coast winter	13	18	24	29	35	40	46	51
	South coast spring	21	26	30	35	39	44	48	53
	South coast autumn	21	26	31	36	42	47	52	65
M. capensis	West coast summer	13	20	26	33	39	46	52	59
	West coast winter	13	17	21	30	40	47	54	61
	South coast spring	13	19	28	38	46	54	63	71
	South coast autumn	13	19	28	36	44	52	61	69

Table 3.A.3: Details for the commercial selectivity-at-length for each fleet (trawl unless otherwise indicated) and species combination for the Reference Case, as well as indications of the nature of the data which are available.

	M. paradoxus		*M. capensis*		Data available
	No of est. parameters	Comments	No of est. parameters	Comments	
1. West coast offshore					
1917-1976	0	average between 77-84 and 93-2013 period	0	average between 77-84 and 93-2013 period	species combined
1977-1984	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	0	as 93-13 but σ_{Left} same difference as for paradoxus btw 77-84 and 93-13 periods	
1985-1992	0	linear change between 1984 and 1993 selectivity	0	linear change between 1984 and 1993 selectivity	
1993-2013	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	0	Based on inshore selectivity: $l_{max}=l_{max}$(inshore)+5, $\sigma_{Left}=\sigma_{Left}$(inshore) and $\sigma_{Right}=3*\sigma_{Right}$(inshore)	
2. South coast offshore					
1917-1976	0	double logistic (σ_{Left}, σ_{Right} and l_{max})	0	average between 77-84 and 93-2013 period	species combined
1977-1984	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	0	as 93-13 but σ_{Left} same difference as for paradoxus btw 77-84 and 93-13 periods	
1985-1992	0	linear change between 1984 and 1993 selectivity	0	linear change between 1984 and 1993 selectivity	
1993-2013	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	0	Based on inshore selectivity: $l_{max}=l_{max}$(inshore)+5, $\sigma_{Left}=\sigma_{Left}$(inshore)	
	0	female downscaling factor (av. of SC spring and autumn surveys's factors)			
3. South coast inshore	-	-	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	*M. capensis*
4. West coast longline					
1984-1999	1	$l_{max}^{84\text{-}99}=l_{max}^{00\text{-}05}-\delta_1^{WCpara}$ (δ_1^{WCpara} estimated, same for males and females)	1	$l_{max}^{84\text{-}99}=l_{max}^{00\text{-}05}-\delta_1^{WCcap}$ (δ_1^{WCcap} estimated, same for males and females)	species and gender combined
2000-2005	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	
	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	species and gender disaggregated
2006-2013	1	$l_{max}^{06\text{-}13}=l_{max}^{00\text{-}05}-\delta_2^{WCpara}$ (δ_2^{WCpara}	1	$l_{max}^{06\text{-}13}=l_{max}^{00\text{-}05}-\delta_2^{WCcap}$ (δ_2^{WCcap}	
	0	estimated, same for males and females)	0	estimated, same for males and females)	
5. South coast longline					
1984-1999	1	$l_{max}^{84\text{-}99}=l_{max}^{00\text{-}05}-\delta_1^{SCpara}$ (δ_1^{SCpara} estimated, same for males and females)	1	$l_{max}^{84\text{-}99}=l_{max}^{00\text{-}05}-\delta_1^{SCcap}$ (δ_1^{SCcap} estimated, same for males and females)	species and gender combined
2000-2005	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	
	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	3	double logistic (σ_{Left}, σ_{Right} and l_{max})	species and gender disaggregated
2006-2013	1	$l_{max}^{06\text{-}13}=l_{max}^{84\text{-}99}-\delta_2^{SCpara}$ (δ_2^{SCpara}	1	$l_{max}^{06\text{-}13}=l_{max}^{84\text{-}99}-\delta_2^{SCcap}$ (δ_2^{SCcap} estimated,	
	0	estimated, same for males and females)	0	same for males and females)	
6. South coast handline	-	-	0	parameters taken as average of SC longline (female, 00-05) and inshore parameters	-
Total	28		19		

Table 3.A.4: Minus- and plus-groups taken for the surveys and commercial proportion at length data.

SURVEY DATA		Sex-aggregated		Males		Females	
		Minus	Plus	Minus	Plus	Minus	Plus
West coast summer	*M. paradoxus*	13	47	20	47	20	47
	M. capensis	13	59	20	59	20	59
West coast winter	*M. paradoxus*	13	51	-	-	-	-
	M. capensis	13	61	-	-	-	-
South coast spring	*M. paradoxus*	21	53	20	53	20	53
	M. capensis	13	71	20	71	20	71
South coast autumn	*M. paradoxus*	21	65	20	59	20	59
	M. capensis	13	69	20	69	20	69

COMMERCIAL DATA		Sex-aggregated		Males		Females	
Fleet	Species	Minus	Plus	Minus	Plus	Minus	Plus
West coast offshore trawl	species combined	23	65	-	-	-	-
South coast offshore trawl	species combined	27	75	-	-	-	-
South coast inshore trawl	*M. capensis*	27	65	-	-	-	-
West coast longline	species combined	45	91	-	-	-	-
	M. paradoxus	-	-	41	85	41	95
	M. capensis	-	-	41	85	41	95
South coast longline	*M. paradoxus*	-	-	41	85	41	80
	M. capensis	45	91	41	95	41	80

Appendix 3.A Addendum

The following are references, tables and figures taken directly from Rademeyer and Butterworth (2014d) that are mentioned in this appendix.

References

Beverton, R.J.H. and Holt, S.J. 1957. On the Dynamics of Exploited Fish Populations. London: Chapman and Hall (facsimile reprint, 1993), 533.

Fournier, D.A., Skaug, H.J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M.N., Nielsen, A., and Sibert, J. 2011. AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. Optim. Methods Softw. 27: 233-249.

Punt, A.E. and Kennedy, R.B. 1997. Population modeling of Tasmanian rock lobster, *Jasus edwardsii*, resources. Mar. Freshw. Res. 48, 967–980.

Singh, L., Melo, Y. and Glazer, J. 2011. *Merluccius capensis* and *M. paradoxus* length-at-50% maturity based on histological analyses of gonads from surveys. Unpublished report. FISHERIES/2011/JUL/SWG-DEM/33.

Singh L. 2013. Length weight relationship of both hake species. Unpublished report. FISHERIES/2013/OCT/SWG-DEM/58.

Smith ADM, Cox S, Parma A and AE Punt. 2013. International Review Panel report for the 2013 International Fisheries Stock Assessment Workshop. 2-6 December 2013, University of Cape Town, South Africa. MARAM/IWS/DEC13/General/4.

Table 3.A.5: Female maturity-at-length ogive (equation 3.A.50) parameter estimates (from Singh *et al.* (2011)).

	$l_{50}(cm)$	$\Delta(cm)$
M. paradoxus	41.53	2.98
M. capensis	53.83	10.14

Table 3.A.6: Length-weight relationship estimates (from Singh (2013)).

	$\alpha(gm/cm^{\beta})$	β
M. paradoxus:		
Males	0.007750	2.977
Females	0.005700	3.071
M. capensis:		
Males	0.006750	3.044
Females	0.005950	3.075

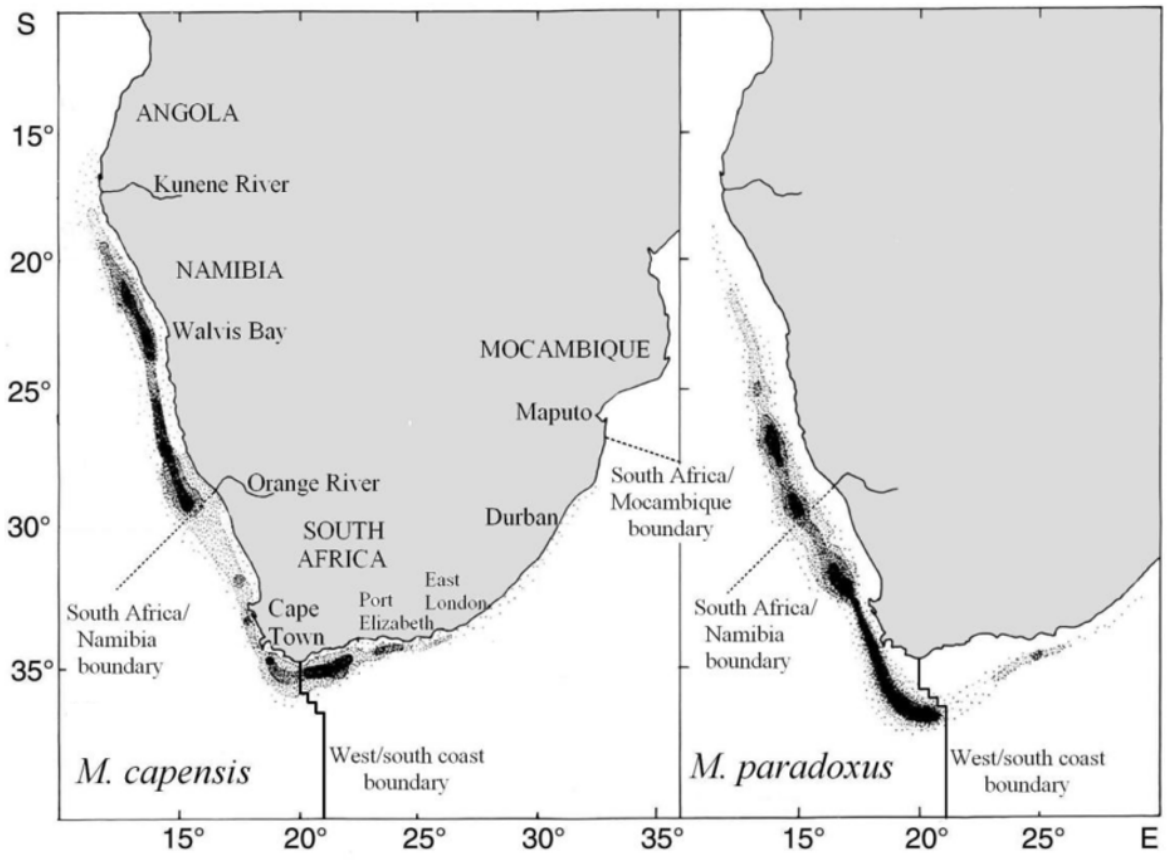

Figure 3.A.2: Management units and species distribution for southern African hake (adapted from Payne (1989)).

3.B Reference Set specifications

These Reference Set specifications are taken from Rademeyer and Butterworth (2014c).

The Reference Set of OMs used in the selection process for OMP-2014 covers three major axes of uncertainty:

1. Centre years for the change from *M. capensis* to *M. paradoxus* preponderance in the catch: 1950, 1958 and 1965.
2. Natural mortality vectors: Mmed ($M_{2-} = 0.75$ and $M_{5+} = 0.375$), Mlow ($M_{2-} = 0.6$ and $M_{5+} = 0.25$) and Mhigh ($M_{2-} = 0.9$ and $M_{5+} = 0.5$).
3. Stock-recruitment relations: Ricker (modified Ricker), BH (Beverton-Holt, h estimated) and BHmod (modified Beverton-Holt).

The modified Ricker relationship is:

$$R_y = \alpha B_y^{sp} e^{(-\beta(B_y^{sp})^{\gamma})} \tag{3.B.1}$$

For the modified Beverton-Holt, the curve below $B^{sp}min$ (the lowest past spawning biomass level) is replaced by the average of that curve and a straight line from the origin to the value of the curve at $B^{sp}min$.

Two concerns arose with this initial set of 27 OMs. The first was that nearly all the associated OMs failed the $-\Delta lnL < 15$ constraint (compared to the best-fitting OM) which had been applied in the past. The large number of OMs in the RS was also a concern (for reasons of computational time), so that only combinations where both the natural mortality vector and the year of the reversal in species dominance were changed from their central choices were included. This led to a revised set of 15 OMs listed in Table 3.B.1.

It was then decided that RS8 and RS9 should be dropped from the revised set because of their questionably small $MSYL/K = 0.11$ value for *M. capensis* , leaving 13 OMs. Finally, RS11 and RS12 were dropped due to their relatively poor fits to the data, with $-\Delta lnL = 23.6$. Dropping these two OMs was also consistent with the approach adopted when developing OMP-2010.

Results for the revised set of OMs can be found in Tables 3.B.2 and 3.B.3, with corresponding spawning biomass trajectories in Figure 3.B.1, median and range spawning biomass trajectories in Figure 3.B.2 and stock-recruitment curves in Figure 3.B.3.

Table 3.B.1: Specifications of revised set of OMs (Rademeyer and Butterworth 2014c).

RS model	Centre year	Natural mortality	Stock-recruitment
RS1 (RC)	1958	Mmed	Ricker
RS2	1958	Mmed	BH
RS3	1958	Mmed	BHmod
RS4	1950	Mlow	Ricker
RS5	1950	Mlow	BH
RS6	1950	Mlow	BHmod
RS7	1950	Mhigh	Ricker
RS8	1950	Mhigh	BH
RS9	1950	Mhigh	BHmod
RS10	1965	Mlow	Ricker
RS11	1965	Mlow	BH
RS12	1965	Mlow	BHmod
RS13	1965	Mhigh	Ricker
RS14	1965	Mhigh	BH
RS15	1965	Mhigh	BHmod

Table 3.B.2: Results for the 15 OMs of the revised set where * and ** indicate models omitted from the final set of 11 OMs (Rademeyer and Butterworth 2014c).

	'Δ-lnL	4.7	6.6	6.6	11.1	13.0	13.0	5.0	5.8	5.8	14.1	23.6	23.6	0.0	10.1	10.1
		RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS8*	RS9*	RS10	RS11**	RS12**	RS13	RS14	RS15
		1958	1958	1958	1950	1950	1950	1950	1950	1950	1965	1965	1965	1965	1965	1965
		Mmed	Mmed	Mmed	Mlow	Mlow	Mlow	Mhigh	Mhigh	Mhigh	Mlow	Mlow	Mlow	Mhigh	Mhigh	Mhigh
		Ricker	BH	BHmod	Ricker	BH	BHmod	Ricker	BH	BHmod	Ricker	BH	BHmod	Ricker	BH	BHmod
	-lnL total	-181.3	-179.4	-179.4	-174.9	-173.0	-173.0	-181.1	-180.2	-180.2	-172.0	-162.4	-162.4	-186.0	-175.9	-175.9
	CPUE historic	-40.0	-39.8	-39.8	-39.1	-39.7	-39.7	-38.1	-36.4	-36.4	-39.2	-38.4	-38.4	-39.2	-39.8	-39.8
	CPUE GLM	-180.7	-179.9	-179.9	-178.6	-176.9	-176.9	-183.0	-183.2	-183.2	-177.0	-169.8	-169.8	-183.4	-175.3	-175.3
	Survey	-32.1	-33.1	-33.1	-35.6	-36.5	-36.5	-31.9	-33.0	-33.0	-36.5	-34.0	-34.0	-33.2	-31.9	-31.9
	Comm. CAL (sex-aggr.): trawl	-42.8	-42.2	-42.2	-42.7	-41.5	-41.5	-38.8	-39.0	-39.0	-38.4	-43.7	-43.7	-42.0	-43.5	-43.5
	longline	-17.2	-17.2	-17.2	-16.1	-17.2	-17.2	-17.2	-17.3	-17.3	-17.1	-17.2	-17.2	-17.3	-17.2	-17.2
	Comm. CAL (sex-disaggr.)	-51.9	-51.8	-51.8	-50.3	-50.3	-50.3	-53.3	-53.1	-53.1	-51.2	-49.5	-49.5	-53.0	-53.2	-53.2
	Survey CAL (sex-aggr.)	-1.8	-1.8	-1.8	0.5	0.8	0.8	-3.6	-3.6	-3.6	-0.1	-1.0	-1.0	-3.8	-3.2	-3.2
	Survey CAL (sex-disaggr.)	42.3	42.5	42.5	45.5	45.5	45.5	43.6	44.3	44.3	45.1	45.2	45.2	43.7	43.6	43.6
	ALK	117.8	118.1	118.1	117.9	117.8	117.8	116.9	116.2	116.2	117.3	118.3	118.3	116.7	117.6	117.6
	Recruitment penalty	8.7	9.7	9.7	7.5	8.8	8.8	9.1	9.3	9.3	7.3	9.8	9.8	9.1	10.2	10.2
	Selectivity smoothing penalty	16.1	15.9	15.9	16.1	16.2	16.2	15.2	15.6	15.6	17.4	17.8	17.8	16.4	16.4	16.4
M. paradoxus	K^{sp}	849	826	826	1697	1821	1821	545	525	525	893	1907	1907	366	468	468
	h	0.91	0.95	0.95	1.02	0.95	0.95	0.82	0.88	0.88	1.70	0.98	0.98	1.20	0.96	0.96
	B^{sp}_{2012}	154	150	150	257	266	266	107	116	116	305	388	388	131	119	119
	B^{sp}_{2012}/K^{sp}	0.18	0.18	0.18	0.15	0.15	0.15	0.20	0.22	0.22	0.34	0.20	0.20	0.36	0.25	0.25
	B^{sp}_{2013}	150	147	147	268	277	277	98	108	108	323	403	403	125	109	109
	B^{sp}_{2013}/K^{sp}	0.18	0.18	0.18	0.16	0.15	0.15	0.18	0.21	0.21	0.36	0.21	0.21	0.34	0.23	0.23
	B^{sp}_{MSY}	153	153	153	412	416	416	100	110	110	343	366	366	114	66	66
	B^{sp}_{MSY}/K^{sp}	0.18	0.18	0.18	0.24	0.23	0.23	0.18	0.21	0.21	0.38	0.19	0.19	0.31	0.14	0.14
	$B^{sp}_{2012}/B^{sp}_{MSY}$	1.00	0.98	0.98	0.62	0.64	0.64	1.07	1.06	1.06	0.89	1.06	1.06	1.15	1.80	1.80
	$B^{sp}_{2013}/B^{sp}_{MSY}$	0.98	0.96	0.96	0.65	0.67	0.67	0.98	0.98	0.98	0.94	1.10	1.10	1.10	1.64	1.64
	MSY	111	111	111	121	120	120	106	111	111	122	119	119	116	110	110
M. capensis	K^{sp}	231	311	311	297	456	456	148	182	182	635	879	879	148	349	349
	h	1.15	0.95	0.95	1.07	0.98	0.98	0.86	0.98	0.98	0.99	0.98	0.98	2.20	0.87	0.87
	B^{sp}_{2012}	142	152	152	173	168	168	96	94	94	417	507	507	109	232	232
	B^{sp}_{2012}/K^{sp}	0.61	0.49	0.49	0.58	0.37	0.37	0.65	0.52	0.52	0.66	0.58	0.58	0.73	0.67	0.67
	B^{sp}_{2013}	158	169	169	193	188	188	107	106	106	451	544	544	121	252	252
	B^{sp}_{2013}/K^{sp}	0.69	0.55	0.55	0.65	0.41	0.41	0.72	0.58	0.58	0.71	0.62	0.62	0.82	0.72	0.72
	B^{sp}_{MSY}	81	53	53	140	82	82	61	20	20	267	158	158	36	68	68
	B^{sp}_{MSY}/K^{sp}	0.35	0.17	0.17	0.47	0.18	0.18	0.41	0.11	0.11	0.42	0.18	0.18	0.24	0.20	0.20
	$B^{sp}_{2012}/B^{sp}_{MSY}$	1.75	2.85	2.85	1.23	2.04	2.04	1.57	4.63	4.63	1.56	3.21	3.21	3.04	3.41	3.41
	$B^{sp}_{2013}/B^{sp}_{MSY}$	1.94	3.17	3.17	1.38	2.28	2.28	1.75	5.22	5.22	1.69	3.44	3.44	3.37	3.70	3.70
	MSY	62	59	59	57	50	41	55	63	44	89	92	69	114	99	99

Table 3.B.3: Lowest, median and highest results for the full 27 OMs of the initial set, the 15 OMs of the revised set, and the two candidates for the final RS: the revised set excluding RS8 and RS9, and the revised set excluding RS8, RS9, RS11 and RS12 (Rademeyer and Butterworth 2014c).

		Initial set			Revised set			Revised set excluding RS8 and RS9			Revised set excluding RS8, RS9, RS11 and RS12		
		Lowest	Median	Highest	Lowest	Median	Highest	Lowest	Median	Highest	Lowest	Median	Highest
	-lnL total	-186.0	-171.4	-154.8	-186.0	-175.9	-162.4	-186.0	-175.9	-162.4	-186.0	-175.9	-172.0
	CPUE historic	-41.0	-38.5	-32.8	-40.0	-39.2	-36.4	-40.0	-39.7	-38.1	-40.0	-39.7	-38.1
	CPUE GLM	-183.4	-175.3	-162.3	-183.4	-178.6	-169.8	-183.4	-177.0	-169.8	-183.4	-178.6	-175.3
	Survey	-36.5	-33.0	-31.8	-36.5	-33.1	-31.9	-36.5	-33.2	-31.9	-36.5	-33.1	-31.9
	Comm. CAL (sex-aggr.): trawl	-47.3	-43.5	-38.7	-43.7	-42.2	-38.4	-43.7	-42.2	-38.4	-43.5	-42.2	-38.4
	longline	-17.4	-17.2	-16.0	-17.3	-17.2	-16.1	-17.3	-17.2	-16.1	-17.3	-17.2	-16.1
	Comm. CAL (sex-disaggr.)	-53.3	-51.7	-49.3	-53.3	-51.8	-49.5	-53.3	-51.8	-49.5	-53.3	-51.8	-50.3
	Survey CAL (sex-aggr.)	-4.1	-2.0	0.8	-3.8	-1.8	0.8	-3.8	-1.8	0.8	-3.8	-1.8	0.8
	Survey CAL (sex-disaggr.)	42.3	44.2	46.4	42.3	44.3	45.5	42.3	43.7	45.5	42.3	43.6	45.5
	ALK	116.2	117.8	119.6	116.2	117.8	118.3	116.7	117.8	118.3	116.7	117.8	118.1
	Recruitment penalty	7.4	9.8	11.9	7.3	9.3	10.2	7.3	9.1	10.2	7.3	9.1	10.2
	Selectivity smoothing penalty	15.2	16.5	18.9	15.2	16.2	17.8	15.2	16.2	17.8	15.2	16.2	17.4
M. paradoxus	K^{sp}	366	849	2510	366	826	1907	366	849	1907	366	826	1821
	h	0.80	0.91	1.43	0.82	0.95	1.70	0.82	0.96	1.70	0.82	0.95	1.70
	B^{sp}_{2012}	107	193	733	107	150	388	107	154	388	107	150	305
	B^{sp}_{2012}/K^{sp}	0.14	0.25	0.38	0.15	0.20	0.36	0.15	0.20	0.36	0.15	0.18	0.36
	B^{sp}_{2013}	98	182	755	98	147	403	98	150	403	98	147	323
	B^{sp}_{2013}/K^{sp}	0.15	0.23	0.40	0.15	0.21	0.36	0.15	0.18	0.36	0.15	0.18	0.36
	B^{sp}_{MSY}	66	162	718	66	153	416	66	153	416	66	153	416
	B^{sp}_{MSY}/K^{sp}	0.12	0.23	0.43	0.14	0.19	0.38	0.14	0.19	0.38	0.14	0.18	0.38
	$B^{sp}_{2012}/B^{sp}_{MSY}$	0.62	1.06	1.97	0.62	1.06	1.80	0.62	1.00	1.80	0.62	0.98	1.80
	$B^{sp}_{2013}/B^{sp}_{MSY}$	0.65	1.01	1.93	0.65	0.98	1.64	0.65	0.98	1.64	0.65	0.96	1.64
	MSY	106	115	124	106	111	122	106	116	122	106	111	122
M. capensis	K^{sp}	148	375	986	148	311	879	148	349	879	148	311	635
	h	0.80	0.95	2.20	0.86	0.98	2.20	0.86	0.98	2.20	0.86	0.98	2.20
	B^{sp}_{2012}	90	232	568	94	168	507	96	168	507	96	168	417
	B^{sp}_{2012}/K^{sp}	0.35	0.61	0.76	0.37	0.58	0.73	0.37	0.58	0.73	0.37	0.61	0.73
	B^{sp}_{2013}	101	252	609	106	188	544	107	188	544	107	188	451
	B^{sp}_{2013}/K^{sp}	0.38	0.68	0.84	0.41	0.62	0.82	0.41	0.65	0.82	0.41	0.69	0.82
	B^{sp}_{MSY}	20	87	278	20	68	267	36	81	267	36	68	267
	B^{sp}_{MSY}/K^{sp}	0.11	0.24	0.43	0.11	0.18	0.47	0.17	0.20	0.47	0.17	0.20	0.47
	$B^{sp}_{2012}/B^{sp}_{MSY}$	1.29	2.54	4.63	1.23	2.85	4.63	1.23	2.85	3.41	1.23	2.04	3.41
	$B^{sp}_{2013}/B^{sp}_{MSY}$	1.42	2.75	5.22	1.38	3.17	5.22	1.38	3.17	3.70	1.38	2.28	3.70
	MSY	44	89	137	41	62	114	41	62	114	41	59	114

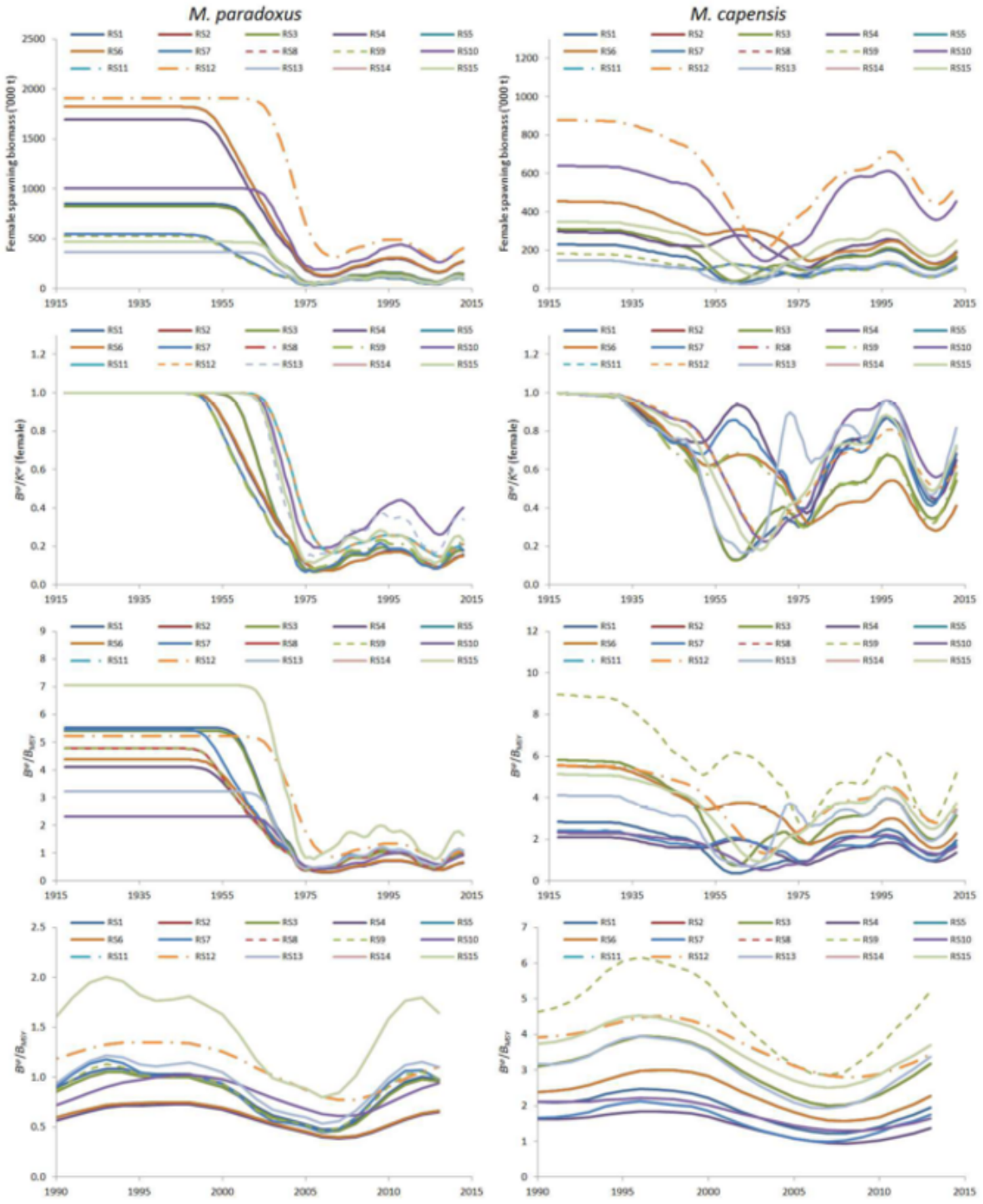

Figure 3.B.1: Female spawning biomass trajectories (in absolute terms - first row -, relative to pre-exploitation level - second row - and relative to MSYL - third and fourth rows) for *M. paradoxus* (left hand column) and *M. capensis* (right hand column) for the 15 OMs of the revised set. The third and fourth rows are the same except for the horizontal axis. Note trajectories for OMs RS3, RS6, RS9, RS12 and RS15 are the same as those for RS2, RS5, RS8, RS11 and RS14 respectively. RS8 and RS9 (dashed lines) and RS11 and RS12 (dashed-dotted lines) were dropped from the final RS (Rademeyer and Butterworth 2014c).

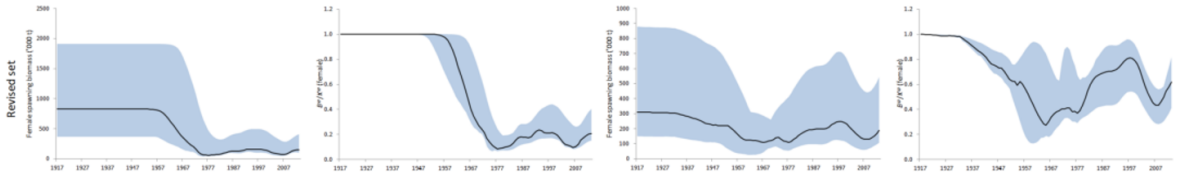

Figure 3.B.2: Median (black line) with minimum-maximum range (shading) spawning biomass trajectories (in absolute terms and relative to pre- exploitation level) for *M. paradoxus* and *M. capensis*, for the 15 OMs of the revised set (Rademeyer and Butterworth 2014c).

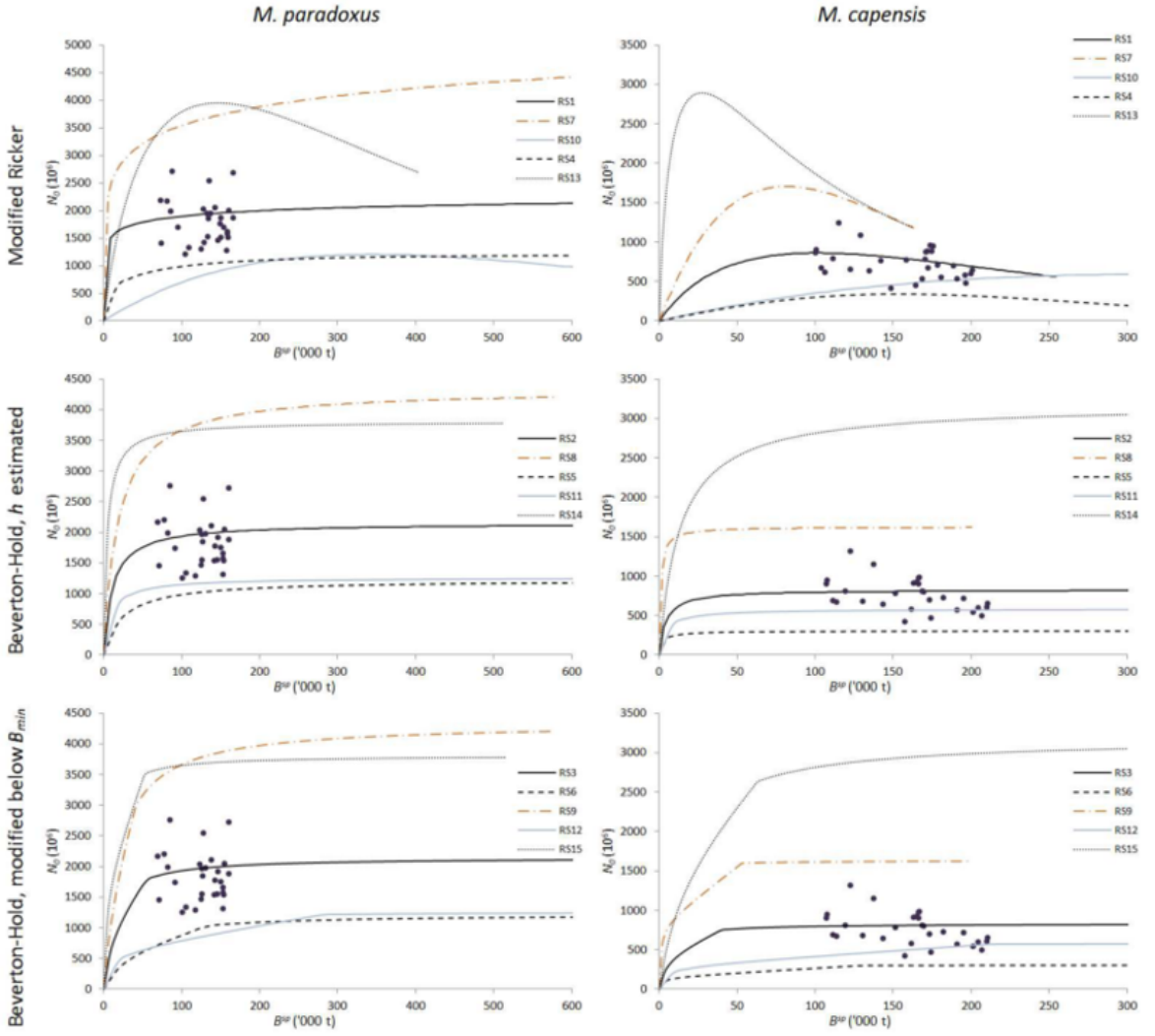

Figure 3.B.3: Estimated stock-recruitment curves for each of the 15 OMs of the revised set for *M. paradoxus* and *M. capensis*, grouped by stock-recruitment curve type. In each plot, the "data" are plotted for a single OM, corresponding to the medium natural mortality and 1958 centre-year (Rademeyer and Butterworth 2014c).

Chapter 4

Data and Methods

4.1 Introduction

Three different inputs were used (spawning biomass, numbers-at-age and CPUE) to compare and find weights for the individual OMs in the RS. As described in detail below, proximity matrices for each input were calculated; these represent the Euclidean distances between each of the OMs. These proximity matrices were used as input to a multidimensional scaling (MDS) algorithm (described in detail in Appendix 4.B) which allows the proximities (intermodel distances/dissimilarities) to be represented in a low-dimensional space. These proximities were input to three of the five different weighting methods (described in Appendix 4.C) used to produce weights (see Table 5.7 of Chapter 5) for each of the OMs in the RS. The resultant weights were then used in Chapter 5 to integrate over these OMs when projecting Catch, $B^{sp}/MSYL^{sp}$, CPUE and Effort forward using OMP-2014.

4.2 Data

4.2.1 Spawning biomass estimates

Spawning biomass (B^{sp}) estimates for both hake species combined (medians over 100 simulations) from each of the OMs over the period (1917-2013) were used (see Table 4.A.1 and Figure 4.1) to compare the OMs. As recommended by Cox *et al.* (2017), only the historical and not the future trends were considered. This is because the historical data alone were sufficient to address the question of differentiating between models.

The Euclidean distances (proximities) were found between each model and all the other models as follows:

$$d_{ij} = \sqrt{\sum_{y=1917}^{2013} (B_{iy}^{sp} - B_{jy}^{sp})^2} \tag{4.2.1}$$

where i and j represent the OMs and y the year.

These distances form a proximity matrix which provides the input required for the MDS method.

4.2.2 Numbers-at-age estimates

The method used to compare the numbers-at-age for each of the OMs, is loosely based on the idea of presence-absence modelling, an example of which is found in Redfern *et al.* (2017) (summarised in Section 2.2.2 of Chapter 2). The simplification of the presence-absence modelling method could have been achieved in multiple ways. In this dissertation, the main idea was to compare models using a 2D framework. In order to achieve this, a numbers-at-age matrix (N_{ya}) was found for each OM in the RS for the time period (1917-2013).

Since the numbers are dominated by the lower ages, it was necessary to transform the matrix as follows to remove this effect:

$$N_{ya}^{*} = N_{ya} e^{Za} \tag{4.2.2}$$

where a and y represent the age and year respectively.

Z was determined by linear regression:

$$lnN_{ya} = lnN_0 - Za \tag{4.2.3}$$

where the parameters N_0 and Z were estimated so that the following function was minimised:

$$\sum_{ya} (lnN_{ya} - lnN_0 + Za)^2 \tag{4.2.4}$$

For each OM, a P_{ya} matrix was calculated as follows:

$$P_{ya} = \begin{cases} 1 & \text{if } N_{ya}^{*} > Av(N_{ya}^{*}) \\ 0 & \text{if } N_{ya}^{*} < Av(N_{ya}^{*}) \end{cases} \tag{4.2.5}$$

where $Av(N_{ya}^{*})$ is the average over both y and a for the corresponding N_{ya}^{*} matrix. The P_{ya} matrix can be considered as a presence-absence output for each OM where 1 represents presence and 0 absence.

For each OM, the P_{ya} matrix was compared to that of each of the other OMs and the number of disagreements (for example, if $P_{1917,1}$ for RS1 is not equal to $P_{1917,1}$ for RS2) were summed. The more disagreements, the more different the OM under consideration from the other OMs. These disagreement numbers were used as proximity data in the MDS process.

4.2.3 CPUE data

For this approach, the logarithms of the observed CPUE data (see Table 3.2 of Chapter 3) were compared to the logs of the model-estimated CPUE trajectories from the South African hake RS OMs from 1955-2012 used to develop OMP-2014. There are six different CPUE data series (2 x ICSEAF CPUEs and 4 x GLM CPUEs) as described in Section 3.3.1.2 of Chapter 3. Logarithms were taken in order to take into account the difference in units. These data series are plotted in Figure 4.2.

The Euclidean distances were found between each model and the observed data as follows:

$$d_{ij} = \sqrt{\sum_{y=1917}^{2012} (lnCPUE_{iy} - lnCPUE_{Obs,y})^2} \tag{4.2.6}$$

where i represents the OMs and y the year.

These distances form a proximity matrix which provides the input for the MDS method.

4.3 Methods

Five different model weighting methods are considered in this dissertation (see Appendix 4.C). Four of the methods have MDS at their base: MDS weight (1), MDS weight (2), the model quality weight and a combination of the MDS weight (2) and model quality weight. The B^{sp} and numbers-at-age estimates are used to illustrate the first two methods, and the CPUE data and estimates are used to determine model quality weights. A fifth set of weights (AIC weights), reflecting the goodness of fit of the OMs to the data, was determined based on the log-likelihood differences for each of the OMs from the best fitting OM.

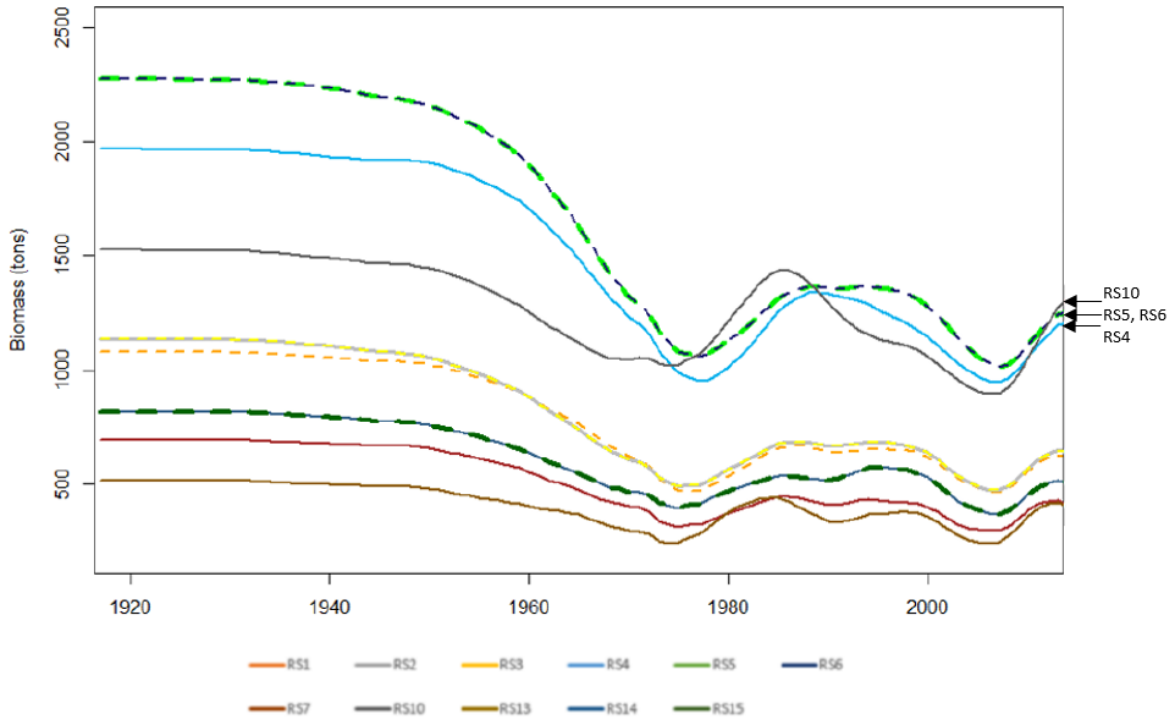

Figure 4.1: Spawning biomass trajectories for both species combined (data in Table 4.A.1) for each of the OMs. RS5, RS6, RS4 and RS10 are the "most different" and therefore have the highest MDS weights.

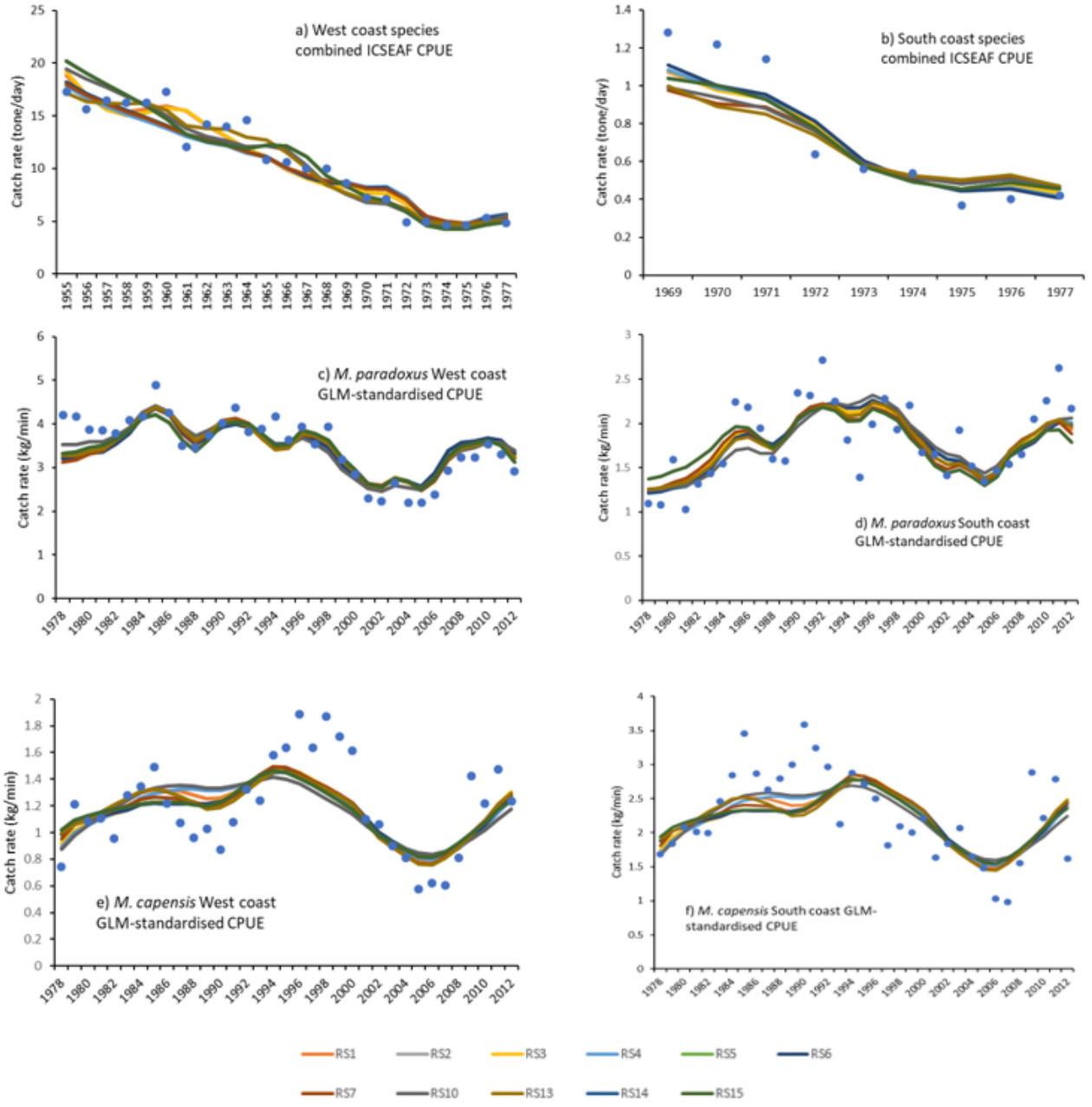

Figure 4.2: Fits to the CPUE data series (Table 3.2 of Chapter 3) generated from the code for the OMP-2014 OMs (details in Chapter 3).

Appendices

4.A Data used for model comparison in Section 4.2.1

Table 4.A.1: Spawning biomass (in thousand tonnes) for both species combined, generated from the code for the OMP-2014 OMs (details in Chapter 3).

Year	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
1917	1080.11	1136.92	1136.92	1970.46	2277.50	2277.74	693.44	1526.94	513.87	816.65	816.65
1918	1079.82	1136.63	1136.63	1970.14	2277.18	2277.42	693.19	1526.62	513.62	816.4	816.40
1919	1079.50	1136.31	1136.31	1969.77	2276.81	2277.06	692.92	1526.25	513.35	816.13	816.13
1920	1078.97	1135.78	1135.78	1969.14	2276.18	2276.42	692.48	1525.61	512.91	815.69	815.69
1921	1079.01	1135.81	1135.81	1969.11	2276.14	2276.58	692.58	1525.57	513.00	815.77	518.77
1922	1078.74	1135.53	1135.53	1968.73	2275.75	2275.99	692.40	1525.18	512.83	815.57	815.57
1923	1078.61	1135.37	1135.37	1968.50	2275.48	2275.73	692.36	1524.93	512.79	815.48	815.48
1924	1078.13	1134.83	1134.83	1967.88	2274.79	2275.03	691.99	1524.70	512.43	815.05	815.05
1925	1077.99	1134.60	1134.60	1967.65	2274.43	2274.67	691.96	1523.98	512.40	814.90	814.90
1926	1077.81	1134.30	1134.30	1967.42	2273.98	2274.23	691.89	1523.64	512.34	814.69	814.69
1927	1077.85	1134.18	1134.18	1967.46	2273.74	2273.98	692.00	1523.56	512.46	814.64	814.64
1928	1078.13	1134.29	1134.29	1967.82	2273.74	2273.98	692.30	1523.76	512.77	814.78	814.78
1929	1077.95	1133.92	1133.92	1967.74	2273.23	2273.48	692.15	1523.51	512.64	814.49	814.49
1930	1077.46	1133.23	1133.23	1967.36	2272.37	2272.62	691.71	1522.93	512.21	813.90	813.90
1931	1076.80	1132.37	1132.37	1966.81	2271.31	2271.56	691.13	1522.17	511.64	813.21	813.21
1932	1076.63	1132.02	1132.02	1966.77	2270.76	2271.01	691.02	1521.92	511.52	812.98	812.98
1933	1073.26	1128.70	1128.47	1963.14	2266.63	2266.88	688.03	1518.09	508.54	809.95	809.95
1934	1070.83	1125.88	1125.88	1960.35	2263.39	2263.63	686.08	1515.12	506.57	807.92	807.92
1935	1067.86	1122.74	122.74	1956.73	2259.36	2259.61	683.80	1511.34	504.28	805.52	805.52
1936	1064.90	1119.57	1119.57	1952.88	2255.11	2255.35	681.70	1507.34	502.18	803.20	803.20
1937	1061.68	1116.04	1116.04	1948.51	2250.26	2250.50	679.52	1502.79	500.01	800.63	800.63
1938	1058.37	1112.24	1112.24	1943.88	2244.95	2245.20	677.39	1497.92	497.94	797.90	797.90
1939	1055.54	1108.67	1108.67	1939.72	2239.76	2240.00	675.80	1493.39	496.44	795.40	795.40
1940	1053.82	1105.91	1105.91	1936.88	2235.37	2235.61	675.24	1489.99	496.04	793.66	793.66
1941	1050.54	1101.25	1101.25	1932.56	2228.81	2229.06	673.23	1484.82	494.25	790.20	790.20
1942	1047.44	1096.47	1096.47	1928.73	2222.02	2222.26	671.34	1479.87	492.64	786.70	786.70
1943	1044.02	1091.08	1091.08	1924.88	2214.42	2214.66	669.10	1474.58	490.72	782.73	782.73
1944	1040.39	1085.29	1085.29	1921.10	2206.20	2206.44	666.64	1469.11	488.58	778.51	778.51
1945	1038.55	1081.18	1081.18	1919.57	2199.68	2199.92	665.72	1465.74	487.99	775.89	775.89
1946	1038.90	1079.19	1079.19	1920.78	2195.44	2195.68	666.61	1465.02	489.20	775.15	775.15
1947	1037.04	1074.85	1074.85	1919.89	2188.61	2188.85	665.29	1462.07	488.22	772.19	772.19
1948	1035.44	1070.73	1070.73	1919.53	2182.08	2182.32	664.09	1459.70	487.36	769.38	769.38
1949	1029.56	1062.24	1062.24	1914.47	2170.66	2170.90	659.02	1452.67	482.64	762.68	762.68
1950	1024.29	1054.45	1054.45	1909.78	2159.82	2160.06	654.73	1466.33	478.63	756.87	756.87
1951	1015.53	1043.24	1043.24	1900.64	2144.80	2145.04	647.61	1435.81	471.74	748.28	748.28
1952	1002.56	1027.91	1027.91	1885.84	2124.58	2124.82	637.27	1419.99	461.61	736.43	736.43
1953	990.52	1013.63	1013.63	1870.83	2104.76	2105	628.48	1404.48	453.14	726.09	726.09
1954	978.60	999.36	999.36	1854.69	2084.15	2084.39	620.38	1388.23	445.72	716.21	716.21
1955	965.17	983.23	983.23	1835.73	2060.68	2060.92	611.37	1369.39	438.01	705.01	705.01

Continued on next page ...

Table 4.A.1: *. . . continued from previous page*

Year	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
1956	950.59	965.44	965.44	1814.49	2034.53	2034.76	601.57	1348.55	430.48	692.69	692.69
1957	936.33	947.49	947.49	1792.74	2007.26	2007.49	592.05	1327.88	424.44	680.68	680.68
1958	920.46	927.45	927.45	1768.27	1976.45	1976.68	580.90	1305.52	418.12	667.28	667.28
1959	903.20	905.77	905.77	1741.02	1942.10	1942.33	568.37	1282.27	411.80	653.00	653.00
1960	881.17	879.08	879.08	1706.65	1899.71	1899.93	551.72	1254.29	402.74	634.86	634.86
1961	854.31	847.47	847.47	1664.28	1848.35	1848.55	531.51	1221.56	391.16	613.10	613.10
1962	830.86	819.49	819.49	1622.42	1796.54	1796.73	515.70	1193.36	384.23	595.25	595.25
1963	809.67	793.96	793.96	1580.44	1743.67	1743.84	502.74	1168.63	379.82	579.88	579.88
1964	784.06	764.31	764.31	1531.92	1683.57	1683.74	486.25	1140.95	371.11	560.95	560.95
1965	761.90	738.94	738.94	1486.15	1625.86	1626	473.89	1120.02	364.42	545.67	545.67
1966	728.80	703.53	703.53	1428.40	1556.12	1556.25	452.25	1091.15	346.93	521.89	521.89
1967	697.61	671.62	671.62	1372.59	1488.55	1488.65	434.27	1067.92	330.13	501.47	501.47
1968	668.78	643.83	643.83	1320.35	1425.22	1425.30	419.70	1051.32	314.69	484.92	484.92
1969	648.15	626.21	626.21	1279.03	1374.20	1374.26	412.74	1047.74	306.10	476.96	476.96
1970	621.53	604.32	604.32	1233.66	1321.42	1321.47	398.96	1042.75	292.98	465.02	465.02
1971	606.96	596.19	596.19	1203.08	1286.24	1286.28	395.31	1054.00	291.69	463.93	463.93
1972	575.08	571.67	571.67	1154.91	1237.04	1237.07	374.44	1050.37	277.36	448.34	448.34
1973	524.63	528.8	528.8	1084.67	1169.25	1169.27	337.57	1026.60	249.85	417.27	417.27
1974	491.37	502.95	502.95	1030.32	1119.74	1119.75	318.72	1019.47	240.38	401.18	401.18
1975	468.43	486.38	486.38	985.64	1081.61	1081.62	308.42	1021.22	241.29	393.28	393.28
1976	469.87	493.02	493.02	968.22	1071.05	1071.05	317.51	1047.14	262.38	404.38	404.38
1977	468.14	494.72	494.72	950.02	1059.19	1059.19	319.35	1067.62	279.23	410.14	410.14
1978	468.47	515.07	515.07	959.05	1072.87	1072.87	336.59	1111.28	311.32	430.14	430.14
1979	510.66	539.87	539.87	981.83	1097.76	1097.77	355.36	1163.03	345.21	451.33	451.33
1980	535.76	564.01	564.01	1014.06	1128.23	1128.23	372.36	1218.09	375.46	468.51	468.51
1981	560.06	586.10	586.10	1053.10	1161.49	1161.50	386.72	1272.46	399.31	482.22	482.22
1982	586.36	609.55	609.55	1100.40	1199.04	1199.06	402.12	1326.3	418.85	496.12	496.12
1983	611.19	631.36	631.36	1150.82	1236.61	1236.64	415.89	1372.85	430.73	508.48	508.48
1984	638.54	656.27	656.27	1207.27	1278.52	1278.54	432.	1414.17	439.14	523.69	523.69
1985	658.22	674.38	674.38	1256.91	1313.60	1313.63	441.19	1436.05	435.87	533.56	533.56
1986	666.09	681.88	681.88	1293.81	1337.48	1337.52	440.53	1434.62	419.91	534.47	534.47
1987	666.38	683.24	683.24	1319.92	1353.24	1353.28	435.15	1414.69	398.36	530.81	530.81
1988	662.46	681.90	681.90	1337.53	1363.79	1363.83	428.52	1383.24	376.69	525.82	525.82
1989	651.35	674.10	674.10	1340.91	1364.15	1364.19	416.56	1340.42	353.23	517.38	517.38
1990	638.77	664.34	664.34	1331.89	1357.21	1357.26	404.99	1290.89	334.35	512.16	512.16
1991	637.05	664.69	664.69	1323.65	1356.43	1356.50	408.16	1245.16	332.1	522.02	552.02
1992	642.25	671.61	671.61	1315.59	1360.28	1360.36	419.00	1206.12	339.95	539.04	539.04
1993	647.96	678.42	678.42	1303.01	1362.86	1362.95	427.84	1176.35	351.41	554.88	554.88
1994	652.75	683.82	683.82	1286.82	1363.55	1363.65	432.32	1155.12	363.27	567.23	567.26
1995	651.87	682.61	682.61	1264.57	1359.00	1359.11	427.86	1136.57	368.21	569.77	569.77
1996	650.20	379.53	679.53	1243.00	1354.12	1354.23	421.50	1125.40	371.91	568.16	568.16
1997	646.77	673.37	673.37	1219.99	1344.54	1344.64	416.78	1113.9	374.81	564.82	564.82
1998	644.95	668.26	668.26	1200.08	1333.48	1333.57	416.98	1102.57	378.03	561.25	561.25
1999	633.78	653.74	653.74	1172.80	1310.03	1310.11	409.65	1082.73	370.43	546.45	546.45

Continued on next page . . .

Table 4.A.1: *... continued from previous page*

Year	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
2000	617.90	634.77	634.77	1144.06	1280.36	1280.43	398.87	1059.42	357.22	526.61	526.61
2001	588.95	602.96	602.96	1105.54	1236.51	1236.57	375.35	1025.18	331.36	494.38	494.38
2002	554.05	564.88	565.88	1064.69	1186.95	1187.01	345.69	988.04	300.31	456.82	456.82
2003	521.80	532.10	532.10	1027.00	1138.48	1138.53	320.20	954.75	273.24	423.27	423.27
2004	498.13	507.29	507.29	995.86	1095.67	1095.73	305.87	927.80	256.12	400.46	400.46
2005	481.72	489.86	489.86	972.21	1060.58	1060.63	299.10	908.29	245.90	385.07	385.07
2006	467.83	475.35	475.35	953.37	1031.09	1031.14	292.22	895.81	239.19	370.89	370.89
2007	463.74	471.22	471.22	946.18	1014.94	1014.98	293.47	898.06	245.10	367.31	367.31
2008	478.63	486.85	486.85	960.82	1023.02	1023.04	311.61	923.32	268.73	381.69	381.69
2009	512.90	522.70	522.70	1001.41	1058.93	1058.92	345.66	976.54	308.56	413.58	413.58
2010	554.42	566.23	566.23	1056.33	1110.36	1110.34	382.74	1049.59	353.16	450.79	450.79
2011	590.17	604.46	604.46	1111.49	1162.59	1162.56	410.76	1129.71	391.18	483.02	83.02
2012	613.43	630.23	630.23	1157.32	1206.00	1205.97	424.10	1204.74	412.48	502.95	502.95
2013	627.00	646.53	646.53	1195.82	1242.34	1242.31	425.56	1272.97	417.59	512.08	512.08

4.B Multidimensional scaling

Multidimensional scaling (MDS) can be very useful in determining perceptual relationships. It allows for the dissimilarities between multiple objects to be visualised in a least-squares representation of the objects in a low-dimensional common space (the space in which the objects are plotted during and after the MDS process). This common space is made up of individual spaces. If there is more than one "source" (measure of nearness), there will be more than one individual space and these spaces can be weighted. In this case, there is only one measure of nearness (the proximity matrix) so that the "new MDS space" will be referred to as the common space. Each object is represented by a point in the common space, where the points are arranged so that the distances between the pairs of points have the strongest possible relation to the dissimilarities among the pairs of objects. (i.e. two similar objects will be close together). As well as interpreting dissimilarities as distances on a plot, MDS can also serve as a dimension reduction technique for high-dimensional data.

There are two different types of MDS: metric (quantitative dissimilarities) or nonmetric (qualitative dissimilarities). Metric, Classical (one proximity matrix with unweighted models) MDS is used in this dissertation and SPSS software (IBM Corp. 2016) is used to perform the MDS using the PROXSCAL (proximity scaling) function which performs MDS of proximity data to find a least-squares representation of the objects in a low-dimensional space. A majorisation algorithm guarantees monotone convergence for optionally transformed, metric or nonmetric data under a variety of models and constraints. Detailed mathematical derivations concerning the algorithm can be found in Commandeur and Heiser (1993).

Input data

Objects that are converted into proximity matrices, or data already in the form of a proximity matrix, are input to the MDS process.

Proximities can be determined from these data in a number of ways: Euclidean distance, Squared Euclidean distance, Chebychev, Block and Minkowski interval measures (IBM Knowledge Center 2012). Euclidean distance is used here as it is the simplest, is sufficient for what is needed and is generally used in Classical MDS. This is done for each of the OM pairs yielding the proximity matrix.

In SPSS, there is also an option to transform the original data before determining the proximities. The transformation options are: z-scores, range -1 to 1, range 0 to 1, maximum magnitude of 1, mean of 1, standard deviation of 1 or no transformation. No transformation was used here so that the absolute as well as the relative scale of the data would be taken into account.

Method

The values in the proximity matrix are then transformed using a simple ratio, an interval, an ordinal or a spline transformation. All transformation functions in PROXSCAL result in nonnegative values for the transformed proximities. The simple ratio transformation (transformed proximities are proportional to the original proximities) is used in this dissertation due to its simplicity and sufficiency for the illustrative task of this exercise.

MDS models ideally require that each proximity value be mapped exactly into its corresponding distance:

$$\hat{d}_{ij} = d_{ij}(X) \tag{4.B.1}$$

where $\hat{d}_{ij}$ are the transformed proximities and $d_{ij}(X)$ are the Euclidean distances between the object points in the common space.

However, the relationship of Equation 4.B.1 is never free of error. Computerised procedures for finding an MDS representation usually start with some initial configuration and improve this configuration by moving its points around in small steps (iteratively) to approximate the ideal model relation (Equation 4.B.1) more and more closely. There are a number of different initial configuration options: simplex, Torgerson, single random start and multiple random start. The single random start is used here due to its simplicity and "randomness". The sensitivity of the final configuration to changing the random starting positions is discussed in Chapter 5.

In order to approximate the ideal model relation, the following raw stress function (Borg and Groenen 2005) is minimised by PROXSCAL for the 11 hake OMs:

$$\sigma_r = \sum_{i<j}^{11} (\hat{d}_{ij} - d_{ij}(X))^2 \tag{4.B.2}$$

with normalised raw stress:

$$\sigma^2 = \sum_{i<j}^{11} (\hat{d}_{ij} - d_{ij}(X))^2 / \sum_{i<j}^{11} (d_{ij}(X))^2 \tag{4.B.3}$$

After evaluation of the stress function, the old function value and the new function values are used to decide whether iterations should continue. If the new function value is smaller than or equal to a minimum stress value set by the user, iterations are terminated. Also, if the difference in consecutive stress values is smaller than or equal to the convergence criterion set by the user, iterations are terminated. Finally, iterations are terminated if the current number of iterations exceeds the maximum number of iteration, also set by the user. In all other cases, iterations continue. Once iterations have been terminated, the final coordinates in the common space are plotted and a distance matrix is produced which shows the distances between the OMs in the common space after the multidimensional scaling.

The normalised stress values for different dimensionalities are given in a scree plot (a plot of stress value against the different numbers of dimensions). With the scree plot, the goal is to find the point where the stress decrements become less pronounced. That point (the "elbow") corresponds to the dimensionality that should be chosen. This is because it marks the point where MDS uses additional dimensions only to better match what amounts to the noise in the data, after having managed to reasonably represent the proximities in the given dimension. In most cases, the smaller the stress value, the better the fit of the MDS distance matrix to the observed distance matrix. Very small stress values can, however, mean that the stress function was in fact not minimised and that there is a problem. This is why it is very important to inspect the final configuration to check if it makes sense. It is important to look for strange patterns and clusters. If the data points in the plot do not follow any pattern, and if the stress plot does not show any clear "elbow", then the data are most likely random "noise".

The more dimensions used to reproduce the distance matrix, the better the fit of the MDS matrix is to the observed matrix (i.e. the smaller the stress). In fact, if as many dimensions as there are variables are used, the proximity matrix can be reproduced perfectly. But the goal is to reduce the complexity and to show the proximity matrix in terms of fewer underlying dimensions.

Another output of the MDS process is a Shepard diagram, which is a scatterplot of the distances between points in the common space against the observed dissimilarities (or proximities). The points in the plot should adhere cleanly to a curve or straight line. It shows how well the proximities have been approximated in the common space. If the scatterplot shows a perfectly straight line, then the proximities would be reproduced perfectly in the common space.

Illustrative example

The following is a simple, hypothetical illustrative example of how MDS works and the related Scree plot and Shepard diagram.

Table 4.B.1 shows the distances/proximities between 7 different elements. MDS was performed on this proximity matrix. From Figure 4.B.1, it can be seen that the Scree plot has "3" as the "elbow". For this reason, it was chosen to represent the proximites between the elements in 3D space after multidimensional scaling (Figure 4.B.3). The relatively straight line form of the Shepard diagram (Figure 4.B.2) shows that the approximation of the proximities in the common space is fairly accurate. The simplicity of this example can lead to less accurate of a representation because the MDS algorithm does not have very much data to work with.

Table 4.B.1: Proximities between elements

	E1	E2	E3	E4	E5	E6	E7
E1	0						
E2	1	0					
E3	5	4	0				
E4	6	3	4	0			
E5	7	4	6	5	0		
E6	4	3	3	6	5	0	
E7	7	4	5	3	4	5	0

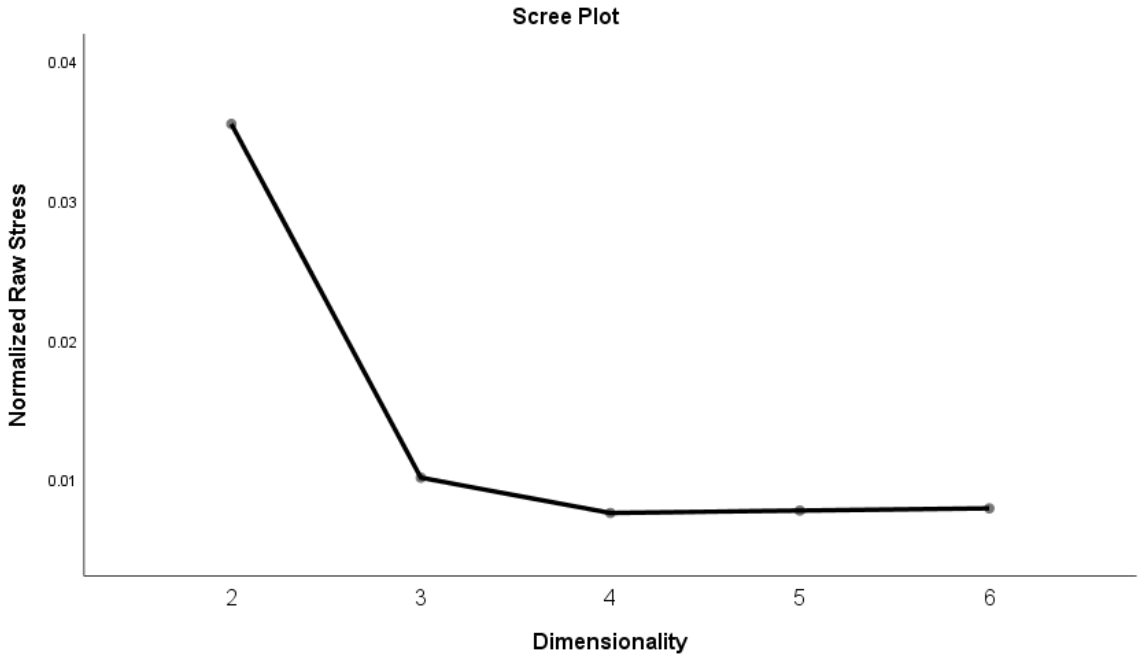

Figure 4.B.1: Scree plot showing the normalised raw stress values.

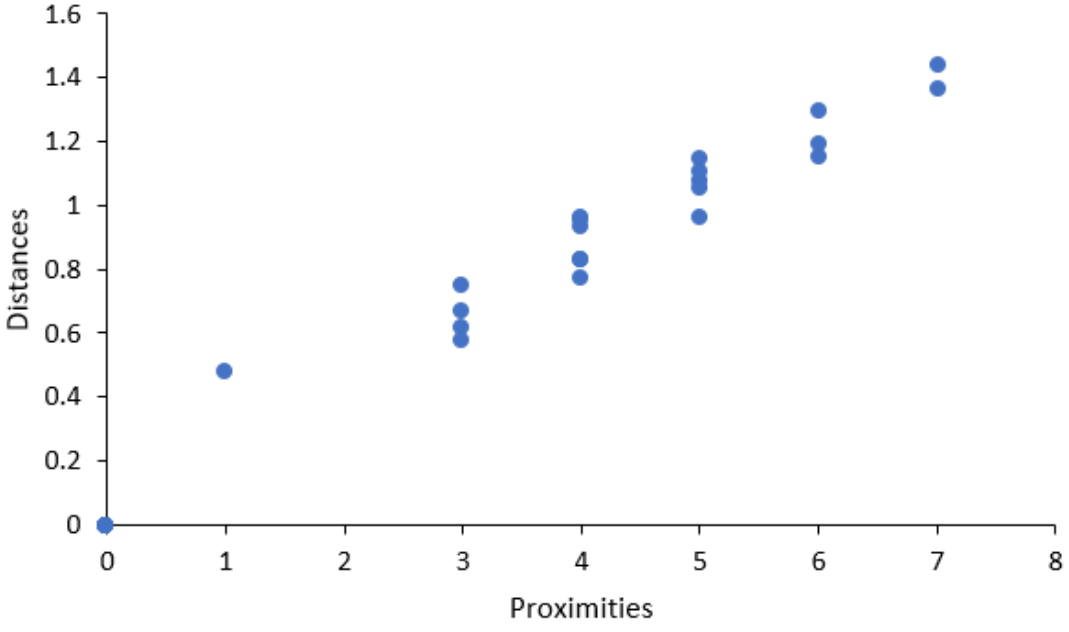

Figure 4.B.2: Shepard diagram for a 3D representation.

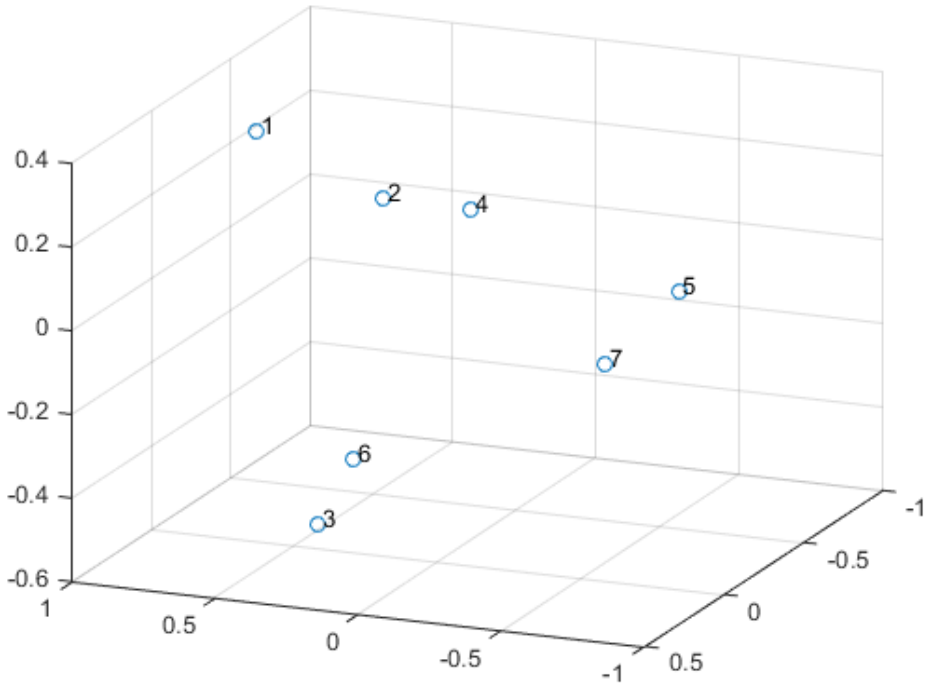

Figure 4.B.3: 3D representation of the proximity matrix for all the elements.

4.C Weighting methods

A number of different weighting methods are illustrated here. All of the weights used in example applications discussed in Chapter 5 are normalised and can be found in Table 5.7.

The first four weighting methods use the intermodel distances determined using MDS (detailed in Appendix 4.B), with the most similar models being downweighted. It is possible to use the original proximities in this case because the data were not transformed in order to determine the proximities, so that the original proximities and the distances after MDS are very similar in relative terms.

4.C.1 MDS weight (1): average distance between models

For each OM in the RS, the average of the distances from that OM to all of the other OMs is calculated and used as a weight.

4.C.2 MDS weight (2): model uniqueness weight

A method described by Sanderson *et al.* (2015a) is used to determine the relative weights for each of the models according to their dissimilarities. The method uses a simple functional form for model similarity:

$$S(d_{ij}) = e^{-(d_{ij}/D_u)^2} \tag{4.C.1}$$

where D_u is a parameter open for choice and is such that model pairs separated by less than this value are considered to be very similar.

Clearly then weights will depend on the value chosen for the D_u parameter. Sanderson *et al.* (2015a) use 10^5 randomly generated ensembles to compare the intermodel distances in the CMIP5 archive (Taylor *et al.* 2012) with distances expected by chance. They define D_u to be the 50th percentile (median) of the nearest-neighbour distances in the set of randomly generated ensembles. In this dissertation, instead of generating a random ensemble, D_u is defined to be the median value of the intermodel distances between the OMs in the common space after multidimensional scaling.

Then, a value for the effective repetition of model i in the ensemble is given by:

$$R_u(i) = 1 + \sum_{j \neq i}^{m} S(d_{ij}) \tag{4.C.2}$$

where m is the total number of models.

A uniqueness weighting (normalised in Table 5.7 following) for each model is then given by:

$$w_u(i) = (R_u(i))^{-1} \tag{4.C.3}$$

In order to test the sensitivity of the weights to the value of the D_u parameter, the weights for each of the RS OMs were calculated using six different values of D_u (Minimum intermodel distance (Min), lower quartile intermodel distance ($Q1$), median intermodel distance ($Q2$), upper quartile intermodel distance ($Q3$), maximum intermodel distance (Max) and five times the maximum distance (5*Max)). This was done separately for the B^{sp} and N_{ya} estimates and the results can be found in Chapter 5.

4.C.3 Model quality weight

Another method described by Sanderson *et al.* (2015a) has been used to determine what they term the "relative model quality" (how well the model fits the data) weights for each of the models.

The model quality weighting is determined as:

$$w_q(i) = e^{-(d_{i(Obs)}/D_q)^2} \tag{4.C.4}$$

where $d_{i(Obs)}$ is the Euclidean distance between the model i and the observation points in the common space and D_q is a free parameter such that if the distance between a model's estimates and the observed data is less than this value, it is considered to be a close fit to the data. This is calculated for the historical data only for which observations are available.

From this equation, it can be seen that the weights depend on the value of the D_q parameter.

Sanderson *et al.* (2015a) made the subjective choice to consider two different values for D_q: a "wide" choice where D_q is equal to the mean intermodel distance in the CMIP5 ensemble (Taylor *et al.* 2012) and a "narrow" choice where D_q is half of that value. The wide case illustrates a situation in which only the models in the ensemble with the largest differences from the data are downweighted, while in the narrow case a distinction is made between the "average" and "best" performers. In this dissertation, D_q is defined to be the median of the distances between each OM and the observation data in the RS.

In order to test the sensitivity of the weights to the value of the D_q parameter, the same method was used as in Section 4.C.2. Thus the weights for each of the RS OMs were determined using six different values of D_q (Min, $Q1$, $Q2$, $Q3$, Max and 5*Max). The CPUE data were used for this approach and the results can be found in Chapter 5.

4.C.4 Combination of MDS weight (2) and model quality weight

Sanderson *et al.* (2015a) made the subjective decision to multiply the two weights together for each model in order to address their goals of removing the influence of exactly replicated models and of models that do not fit the data well. This method is used in this dissertation as an illustration of how to take these two model characteristics into account:

$$w_{comb}(i) = w_u(i)w_q(i) \tag{4.C.5}$$

where i represents the OM.

4.C.5 AIC likelihood weight

A fifth set of weights (AIC weights, reflecting goodness of fit of the OM to the data) is computed based on the log-likelihood differences for each of the OMs compared to the best fitting OM:

$$w_i = e^{-(\Delta(-lnL))_i} \tag{4.C.6}$$

where i represents the OM.

Chapter 5

Results and Discussion

5.1 Introduction

This chapter presents the results of the main analyses and methods described in Chapter 4. Section 5.2.1 gives the results of the MDS analyses with proximity matrices, distance matrices (distances in the common space), Scree plots, Shepard diagrams and 3D representations of the proximity matrices given for each of the three input sources mentioned in Chapter 4. Section 5.2.2 gives the different weights for each of the RS OMs obtained using the weighting methods described in Appendix 4.C. The projections using the weighted RS with OMP-2014 can be found in Section 5.2.3. A discussion regarding these results follows in Section 5.3.

5.2 Results

5.2.1 Multidimensional scaling

MDS was performed on each of the proximity matrics (see Tables 5.1, 5.3 and 5.5) from the three different inputs, as described in Chapter 4. In all three cases, it was decided to represent the OMs in 3D space. The Scree plots for the B^{sp} and N_{ya} estimates clearly (Figures 5.1 and 5.4) have "3" as the "elbow". In the Scree plot for the CPUE data (Figure 5.7), the "elbow" seems to be at "4" rather than at "3", but three dimensions are easier to interpret visually. If the goal is to use MDS to transform the data more than to visualise the dissimilarities, then four dimensions should be chosen.

For the spawning biomass estimates (B^{sp}), the Scree plot, Shepard diagram and 3D representations are given in Figures 5.1 – 5.3 respectively. Table 5.1 presents the proximities and Table 5.2 the distances between OMs in 3D space after multidimensional scaling. The MDSs outputs for the numbers-at-age (N_{ya}) estimates can be found in Figures 5.4-5.6, with proximities and distances in Tables 5.3 and 5.4 respectively. Similarly, the CPUE proximities and distances are in Tables 5.5 and 5.6 with Figures 5.7 - 5.9 showing the outputs.

Note that the units are arbitrary for the proximity and distance matrices and that the orientation of the common space axes is also arbitrary. Also note that there is no "distance" between a model and itself, which is why there are zeros on the diagonal. The off-diagonal zeros in the proximity matrices are due to the fact that the

two OMs are identical except for the stock-recruitment relationship which does not affect the historical values used in calculating distances.

5.2.2 Weights

The weights were determined using the methods described in Chapter 4. All the different weights are listed in Table 5.7, and Figures 5.10 - 5.13 show the differences between the weights calculated using the different methods. The subscripts in the RS OM column in Table 5.7 show closely related models. In all cases, the only factor that varies between these closely related models is the stock-recruitment relationship. A detailed explanation of the RS can be found in Appendix 3.B.

Tables 5.8-5.10 and Figures 5.14-5.16 show the sensitivity of the weights to different values of D_u and D_q (see Equations 4.C.1 and 4.C.4 in Appendix 4.C). The weights for each of the RS OMs were calculated using six different values (Minimum intermodel distance (Min), lower quartile intermodel distance (Q1), median intermodel distance (Q2), upper quartile intermodel distance (Q3), maximum intermodel distance (Max) and five times the maximum distance (5^* Max)). This was done separately for the three (B^{sp}, N_{ya} and CPUE) inputs.

5.2.3 Projections

OMP-2014 was projected using the various weighting options for the OMs shown in Table 5.7. Figures 5.17-5.20 show the comparison of the OMP-2014 projections between the equally weighted and unequally weighted averages for the B^{sp}, N_{ya} and CPUE input types as well as using AIC weights.

In order to weight the projections from each of the OMs, random numbers were drawn from a uniform distribution and these numbers dictated from which OM a projection would be taken based on the OM weights. Since using random numbers causes variation in the projections, the process was repeated ten times. There was a small amount of Monte Carlo variation associated with the ten projections so it was decided that the average would be used. This process was repeated for each set of weights.

Since a key consideration in Marine Stewardship Council certification of the hake trawl fishery has been the time the *M. paradoxus* population will take to reach MSYL, the year in which each projection median predicts the popultion reaching MSYL is compared for the different weights and input types. These results can be found in Table 5.11.

5.3 Discussion

5.3.1 Multidimensional scaling

The single random start is used as an initial configuration in the common space for the MDS process (see Appendix 4.B). As with all minimisations, there is no guarantee that a minimum has been reached. Ideally, the MDS would be repeated for a number of starting points and the result chosen would be the one that has the smallest stress value. MDS is not necessary to get weights - the proximity matrix can be used - therefore there

is less "error" in weights if proximities are used, but the use of MDS distances also allows for transformations and normalisation of inputs.

Some key points regarding the proximity and distance matrices and the 3D representations thereof are as follows.

1. If a proximity matrix contains off-diagonal zeros, it means the model pair is identical in terms of the method of comparison used. This is the case for RS2 and RS3, RS5 and RS6, and RS14 and RS15. This is shown in the 3D representations in which these model pairs overlap one another.
2. When comparing the proximity and distance matrices for each input, it can be seen that the proximities have been scaled downwards to fit into the common space, and that the proximities are not represented exactly, although closely. This slight error is related to the non-zero stress value, which is discussed below.
3. From the 3D representations for the B^{sp} and N_{ya} inputs, it can be seen that RS4, RS5, RS6 and RS10 are the "furthest away" from the other OMs. From the proximity and distance matrices for the CPUE input, it is clear that RS10, RS14, RS15, RS5 and RS6 are the "furthest" from the CPUE data (Obs).

For the B^{sp} and N_{ya} Shepard diagrams for the 3D representations, it is evident that the points lie on an almost straight line where the gradient of the line is equal to the ratio used to transform the proximities (see Figures 5.2 and 5.5). This reflects that the proximities have been reproduced very well in the common space. The Shepard diagram for the CPUE data is not as close to a straight line as the previous two (Figure 5.8). This is because for 3D representations the stress value is higher after the MDS for the CPUE compared to the other estimates (see Scree plots: Figures 5.1, 5.4 and 5.7).

5.3.2 Weights

The intermodel distances determined using MDS are used to determine the weights instead of proximities because, in general, transformations of the input data (which MDS can accommodate) helps to avoid imbalances in the inputs from outliers.

In general, the more similar an OM to the other OMs for the B^{sp} and N_{ya} inputs, the smaller the weight. This is in line with the aim of the method which is to downweight similar models. In contrast, the CPUE model quality weights are higher for OMs that are "closer" to the CPUE data (Obs) because OMs that fit the data better should have more of an influence on the overall averaged projections. The combination weights allow both the similarity of the OMs in the RS and the fit of the OMs to the data to be taken into account, with the method of combining the two weights being a subjective choice.

The AIC weights are very different from the MDS weights, spanning a much greater range. RS13 (which fits the data best) has a (very) high weight, but RS10 corresponds to the worst fit to the data of all the OMs and gets effectively zero weight. The difference between the model quality weights and the AIC is due to the fact that the AIC weight takes the fit of the OMs to all the data into account rather than how well the OMs fit the CPUE data alone. The AIC weighting scheme is not recommended here as it relies upon assumptions that are unlikely to be valid, in particular in this case that all data used in fitting the OMs are independent. This method is, however, included here as an illustration and to allow a comparison with the other weighting schemes.

From Tables 5.8-5.10 and Figures 5.14-5.16, it can be seen that the weights are sensitive to the values chosen for D_u and D_q. Since D_u and D_q are "radii of similarity", the OM pairs that are separated by less than the

parameter value are considered to be similar; therefore as the parameter values increase, increasingly distant pairs of OMs are considered similar with those pairs being increasingly downweighted. From Equations 4.C.1-4.C.3, it can be seen that the smaller the intermodel distance is compared to the value of D_u, the larger the value of S (a measure of model similarity) will be. The more large values of S there are for an OM, the smaller the weight. For the CPUE data, it can be seen from Equation 4.C.4 that the smaller the distance between the OM and the data (Obs) is compared to the value of D_q, the larger the weight.

Some important aspects to note regarding the sensitivity of the weights to the values of D_u and D_q are as follows.

1. For the 5^{th} percentile values of D_u and D_q, only the OM pairs with intermodel distances less than these parameter values are considered similar and are downweighted slightly. The rest of the models are considered to be dissimilar and have larger relative weights.

2. When the values of the D_u and D_q parameters are 5^*Max, all the models are considered to be similar and have very similar weights.

3. The median D_u and D_q values were used to calculate the final weights because this is in essence the same approach as in Sanderson *et al.* (2015a) and because it allows for a reasonably wide range of weights which helps to visualise the way in which this weighting method works.

5.3.3 Projections

When using the weights produced from the B^{sp} estimates, the weighted RS provided a lower spawning biomass projection for *M. paradoxus* than the equally weighted RS used to select the current hake OMP in 2014 (Figure 5.17). This suggests that, had some unequal weighting approach been used in 2014, it might have led to the selection of a slightly more conservative OMP, which would have set catches lower. When using the weights produced from the N_{ya} estimates, the spawning biomass projections are very similar to the equally weighted RS (Figure 5.18); therefore weighting on that basis would not have made a very big difference to the selection of the OMP. When using the CPUE model quality weights, the weighted RS provided a lower spawning biomass projection for *M. paradoxus* than the equally weighted RS used to select the current hake OMP in 2014 (Figure 5.19). As is the case with the weights produced from the B^{sp} estimates, this might have led to the selection of a slightly more conservative OMP. The projection using the AIC weights provides a much higher spawning biomass projection for *M. paradoxus* than the equally weighted RS used to select the current hake OMP in 2014 on average (Figure 5.20). If these weights were used in 2014, a much less conservative OMP, allowing for more catches to be taken, would have been selected.

These relationships between the equally and unequally weighted average projections are reflected in Table 5.11. Of all the unequally weighted averages, the only one in which the spawning biomass for *M. paradoxus* is projected to reach MSYL sooner than the equally weighted average (two years earlier) is the AIC weighted projection. The others predict the population to reach MSYL at the same time or a year later than the equally weighted OMP-2014 projection.

Table 5.1: $\mathbf{B^{sp}}$ proximities between the hake OMs calculated using the Euclidean distance.

	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
RS1	0										
RS2	341.438	0									
RS3	341.438	0	0								
RS4	7264.637	6994.767	6994.767	0							
RS5	9177.755	8898.983	8898.983	2002.135	0						
RS6	9179.342	8900.567	8900.567	2003.786	0	0					
RS7	2944.812	3230.281	3230.281	10201.882	12121.038	12122.628	0				
RS10	4872.346	4629.636	4629.636	3277.053	5170.837	5172.515	7632.634	0			
RS13	4182.621	4466.519	4466.519	11416.447	13346.523	13348.125	1272.739	8746.869	0		
RS14	1972.146	2251.369	2251.369	9205.638	11129.359	11130.957	1029.778	6625.636	2228.085	0	
RS15	1972.146	2251.369	2251.369	9205.638	11129.359	11130.957	1029.778	6625.636	2228.085	0	0

Table 5.2: Distances (found using $\mathbf{B^{sp}}$ values) between OMs in 3D space after application of MDS.

	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
RS1	0										
RS2	0.047	0									
RS3	0.047	0	0								
RS4	1.046	1.007	1.007	0							
RS5	1.321	1.279	1.279	0.287	0						
RS6	1.321	1.280	1.280	0.287	0	0					
RS7	0.426	0.468	0.468	1.459	1.735	1.735	0				
RS10	0.690	0.660	0.660	0.468	0.744	0.744	1.093	0			
RS13	0.601	0.642	0.642	1.631	1.905	1.905	0.179	1.271	0		
RS14	0.281	0.324	0.324	1.318	1.594	1.595	0.145	0.952	0.322	0	
RS15	0.281	0.324	0.324	1.318	1.594	1.595	0.145	0.952	0.322	0	0

Table 5.3: Numbers-at-age ($\mathbf{N_{ya}}$) proximities between the hake OMs calculated using the method described in Section 4.2.2 of Chapter 4.

	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
RS1	0										
RS2	26	0									
RS3	26	0	0								
RS4	137	157	157	0							
RS5	107	125	125	32	0						
RS6	107	125	125	32	0	0					
RS7	66	46	46	201	171	171	0				
RS10	219	239	239	84	114	114	285	0			
RS13	45	35	35	168	142	142	61	228	0		
RS14	34	10	10	155	127	127	52	237	35	0	
RS15	34	10	10	155	127	127	52	237	35	0	0

Table 5.4: Distances (found using $\mathbf{N_{ya}}$ values) between the hake OMs in 3D space after application of MDS.

	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
RS1	0										
RS2	0.206	0									
RS3	0.206	0	0								
RS4	1.070	1.223	1.223	0							
RS5	0.845	0.989	0.989	0.246	0						
RS6	0.845	0.989	0.989	0.246	0	0					
RS7	0.512	0.367	0.367	1.573	1.339	1.339	0				
RS10	1.683	1.841	1.841	0.665	0.906	0.906	2.193	0			
RS13	0.356	0.279	0.279	1.289	1.077	1.077	0.477	1.851	0		
RS14	0.260	0.080	0.080	1.223	0.988	0.988	0.402	1.838	0.276	0	
RS15	0.260	0.080	0.080	1.223	0.988	0.988	0.402	1.838	0.276	0	0

Table 5.5: CPUE proximities between estimates from the OMs and data (Obs) using Euclidean distances.

	Obs	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
Obs	0											
RS1	2.805	0										
RS2	2.848	0.417	0									
RS3	2.848	0.417	0	0								
RS4	2.882	0.576	0.658	0.658	0							
RS5	2.910	0.644	0.486	0.486	0.505	0						
RS6	2.910	0.644	0.486	0.486	0.505	0	0					
RS7	2.842	0.628	0.600	0.600	0.723	0.660	0.660	0				
RS10	2.949	0.920	1.041	1.041	0.936	1.079	1.079	1.157	0			
RS13	2.799	0.719	0.765	0.765	0.996	0.913	0.913	0.694	0.944	0		
RS14	2.938	0.960	0.939	0.939	1.185	1.000	1.000	0.907	1.162	0.924	0	
RS15	2.938	0.960	0.939	0.939	1.185	1.000	1.000	0.907	1.162	0.924	0	0

Table 5.6: Distances (found using **CPUE data (Obs) and model estimates**) between the hake OMs in 3D space after application of MDS.

	Obs	RS1	RS2	RS3	RS4	RS5	RS6	RS7	RS10	RS13	RS14	RS15
Obs	0											
RS1	1.859	0										
RS2	2.083	0.251	0									
RS3	2.083	0.251	0	0								
RS4	2.014	0.356	0.462	0.462	0							
RS5	2.222	0.386	0.285	0.285	0.320	0						
RS6	2.223	0.386	0.285	0.285	0.320	0	0					
RS7	1.796	0.275	0.403	0.403	0.481	0.499	0.499	0				
RS10	2.103	0.762	0.833	0.833	0.598	0.672	0.672	0.619	0			
RS13	1.906	0.475	0.432	0.432	0.795	0.675	0.674	0.411	0.976	0		
RS14	2.180	0.757	0.686	0.686	0.898	0.736	0.736	0.558	0.737	0.541	0	
RS15	2.180	0.757	0.686	0.686	0.898	0.736	0.736	0.558	0.737	0.541	0	0

Table 5.7: Model weights - where subscripts show "similar" models. If each of the 11 OMs were equally weighted, this weight would be $1/11 = 0.0909$. Log-likelihood values (Rademeyer and Butterworth 2014c) relative to the best fitting OM (RS13) are also given with their associated AIC weights. MDS weight (1) refers to the weights determined using the distance averaging method and MDS weight (2) refers to the weights found using the model uniqueness weighting method (B^{sp} [$D_u = 0.690$] and N_{ya} [$D_u = 0.906$]). The model quality weight refers to the weights determined by comparing the CPUE data with the CPUE OM estimates ($D_q = 2.083$) and the two "combination" weights are the product of the MDS (2) and the model quality weights. All weights have been normalised to sum to one over the 11 OMs.

RS OM	Centre year	Natural mortality	Stock-recruitment	B^{sp} MDS weight (1)	B^{sp} MDS weight (2)	N_{ya} MDS weight (1)	N_{ya} MDS weight (2)	CPUE model quality weight	B^{sp} combi-nation	N_{ya} combi-nation	$\Delta(-lnL)$	AIC weight
$RS1_{RS2,RS3}$ (RC)	1958	Mmed	Ricker	0.067	0.068	0.070	0.067	0.108	0.082	0.081	4.700	0.009
$RS2_{RS1,RS3}$	1958	Mmed	BH	0.067	0.069	0.068	0.067	0.088	0.068	0.066	6.600	0.001
$RS3_{RS1,RS2}$	1958	Mmed	BHmod	0.067	0.069	0.068	0.067	0.088	0.068	0.066	6.600	0.001
$RS4_{RS5,RS6}$	1950	Mlow	Ricker	0.108	0.116	0.112	0.111	0.094	0.122	0.116	11.100	0
$RS5_{RS4,RS6}$	1950	Mlow	BH	0.129	0.133	0.094	0.095	0.077	0.115	0.081	13.000	0
$RS6_{RS4,RS5}$	1950	Mlow	BHmod	0.130	0.133	0.094	0.095	0.077	0.115	0.081	13.000	0
$RS7$	1950	Mhigh	Ricker	0.087	0.074	0.101	0.082	0.114	0.094	0.104	5.000	0.007
$RS10$	1965	Mlow	Ricker	0.091	0.113	0.175	0.206	0.087	0.110	0.200	14.100	0
$RS13_{RS14,RS15}$	1965	Mhigh	Ricker	0.104	0.089	0.081	0.073	0.104	0.104	0.085	0	0.982
$RS14_{RS13,RS15}$	1965	Mhigh	BH	0.076	0.068	0.069	0.068	0.080	0.061	0.061	10.100	0
$RS15_{RS13,RS14}$	1965	Mhigh	BHmod	0.076	0.068	0.069	0.068	0.080	0.061	0.061	10.100	0

Table 5.8: B^{sp} MDS weight (2) with different $\mathbf{D_u}$ values (given in parentheses): 5^{th} percentile intermodel distance (5^{th} P), lower quartile intermodel distance (Q1), median intermodel distance (Q2), upper quartile intermodel distance (Q3), maximum intermodel distance (Max) and five times the maximum distance (5*Max), where the intermodel distances are taken from the distance matrix (Table 5.2).

RS OM	5^{th} P (0.033)	Q1 (0.323)	Q2 (0.690)	Q3 (1.299)	Max (1.905)	5*Max (9.525)
$RS1_{RS2,RS3}$ (RC)	0.102	0.060	0.068	0.077	0.083	0.091
$RS2_{RS1,RS3}$	0.061	0.064	0.069	0.077	0.083	0.091
$RS3_{RS1,RS2}$	0.061	0.064	0.069	0.077	0.083	0.091
$RS4_{RS5,RS6}$	0.129	0.122	0.116	0.100	0.095	0.091
$RS5_{RS4,RS6}$	0.065	0.101	0.133	0.120	0.107	0.092
$RS6_{RS4,RS5}$	0.065	0.101	0.133	0.120	0.107	0.092
$RS7$	0.129	0.065	0.074	0.086	0.089	0.091
$RS10$	0.129	0.211	0.113	0.086	0.087	0.091
$RS13_{RS14,RS15}$	0.129	0.097	0.089	0.094	0.094	0.091
$RS14_{RS13,RS15}$	0.065	0.057	0.068	0.081	0.086	0.091
$RS15_{RS13,RS14}$	0.065	0.057	0.068	0.081	0.086	0.091

Table 5.9: N_{ya} MDS weight (2) with different $\mathbf{D_u}$ values (given in parentheses): 5^{th} percentile intermodel distance (5^{th} P), lower quartile intermodel distance (Q1), median intermodel distance (Q2), upper quartile intermodel distance (Q3), maximum intermodel distance (Max) and five times the maximum distance (5*Max), where the intermodel distances are taken from the distance matrix (Table 5.4).

RS OM	5^{th} P (0.056)	Q1 (0.276)	Q2 (0.906)	Q3 (1.223)	Max (2.193)	5*Max (10.967)
$RS1_{RS2,RS3}$ (RC)	0.129	0.070	0.079	0.074	0.085	0.091
$RS2_{RS1,RS3}$	0.057	0.045	0.081	0.075	0.086	0.091
$RS3_{RS1,RS2}$	0.057	0.045	0.081	0.075	0.086	0.091
$RS4_{RS5,RS6}$	0.129	0.118	0.098	0.103	0.094	0.091
$RS5_{RS4,RS6}$	0.064	0.092	0.089	0.090	0.089	0.091
$RS6_{RS4,RS5}$	0.064	0.092	0.089	0.090	0.089	0.091
$RS7$	0.129	0.135	0.091	0.088	0.092	0.091
$RS10$	0.129	0.224	0.148	0.174	0.120	0.092
$RS13_{RS14,RS15}$	0.129	0.083	0.083	0.079	0.087	0.091
$RS14_{RS13,RS15}$	0.057	0.047	0.081	0.076	0.086	0.091
$RS15_{RS13,RS14}$	0.057	0.047	0.081	0.076	0.086	0.091

Table 5.10: CPUE model quality weights with different $\mathbf{D_q}$ values (given in parentheses): 5^{th} percentile intermodel distance (5^{th} P), lower quartile intermodel distance (Q1), median intermodel distance (Q2), upper quartile intermodel distance (Q3), maximum intermodel distance (Max) and five times the maximum distance (5*Max), where the intermodel distances are taken from the distance matrix (Table 5.6).

RS OM	5^{th} P (1.828)	Q1 (1.960)	Q2 (2.083)	Q3 (2.180)	Max (2.223)	5*Max (11.115)
$RS1_{RS2,RS3}$ (RC)	0.114	0.111	0.108	0.107	0.106	0.092
$RS2_{RS1,RS3}$	0.087	0.088	0.088	0.089	0.089	0.091
$RS3_{RS1,RS2}$	0.087	0.088	0.088	0.089	0.089	0.091
$RS4_{RS5,RS6}$	0.095	0.095	0.094	0.094	0.094	0.091
$RS5_{RS4,RS6}$	0.073	0.075	0.077	0.078	0.079	0.090
$RS6_{RS4,RS5}$	0.073	0.075	0.077	0.078	0.079	0.090
$RS7$	0.122	0.118	0.114	0.112	0.111	0.092
$RS10$	0.085	0.086	0.087	0.087	0.087	0.091
$RS13_{RS14,RS15}$	0.108	0.106	0.104	0.103	0.102	0.091
$RS14_{RS13,RS15}$	0.077	0.079	0.080	0.081	0.082	0.091
$RS15_{RS13,RS14}$	0.077	0.079	0.080	0.081	0.082	0.091

Table 5.11: Comparison of years when the median spawning biomass for *M. paradoxus* is projected to reach MSYL for the different weighting approaches. Using the equally weighted RS, OMP-2014 projects the spawning biomass to reach MSYL in 2023. The values in parentheses represent the difference between this year and the years predicted using the unequally weighted RSs.

	MDS weight (1)	MDS weight (2)	Combination	Model quality weight	AIC weight
B^{sp}	2024 (+1)	2024 (+1)	2024 (+1)	-	-
N_{ya}	2023 (0)	2023 (0)	2023 (0)	-	-
CPUE	-	-	-	2024 (+1)	-
Fit to data	-	-	-		2021 (-2)

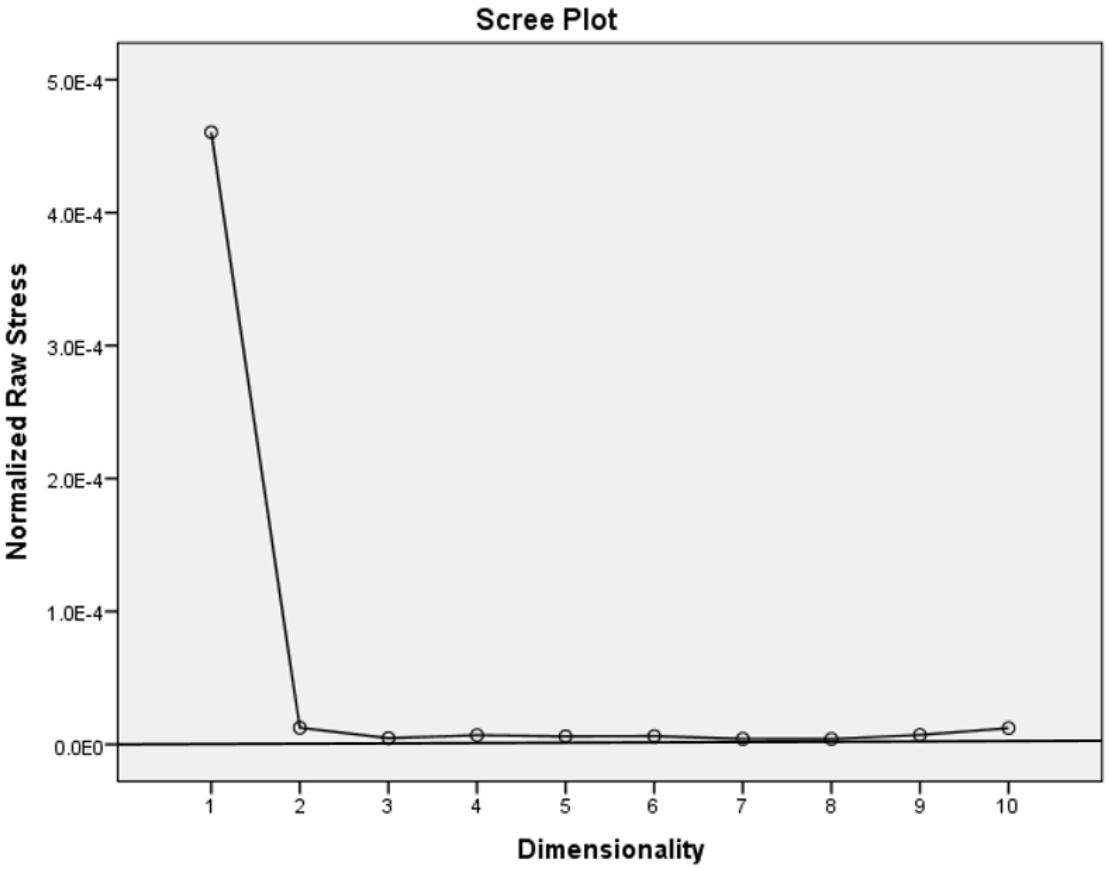

Figure 5.1: Scree plot for $\mathbf{B}^{\mathbf{sp}}$ showing the normalised raw stress values.

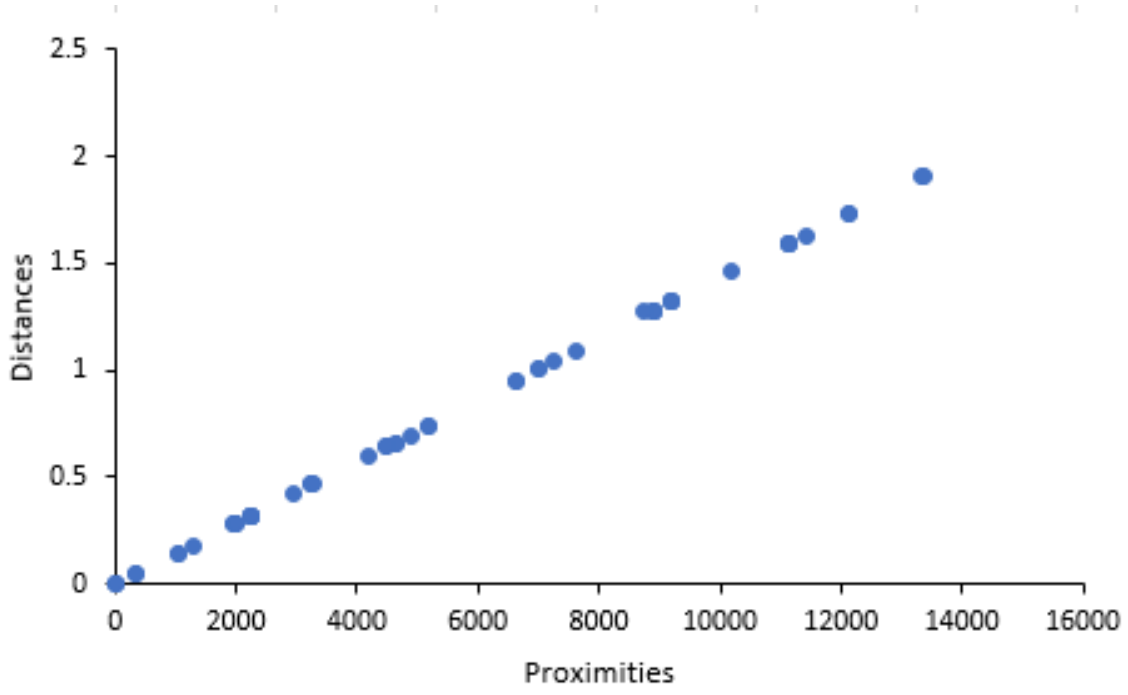

Figure 5.2: Shepard diagram for $\mathbf{B}^{\mathbf{sp}}$ for a 3D representation.

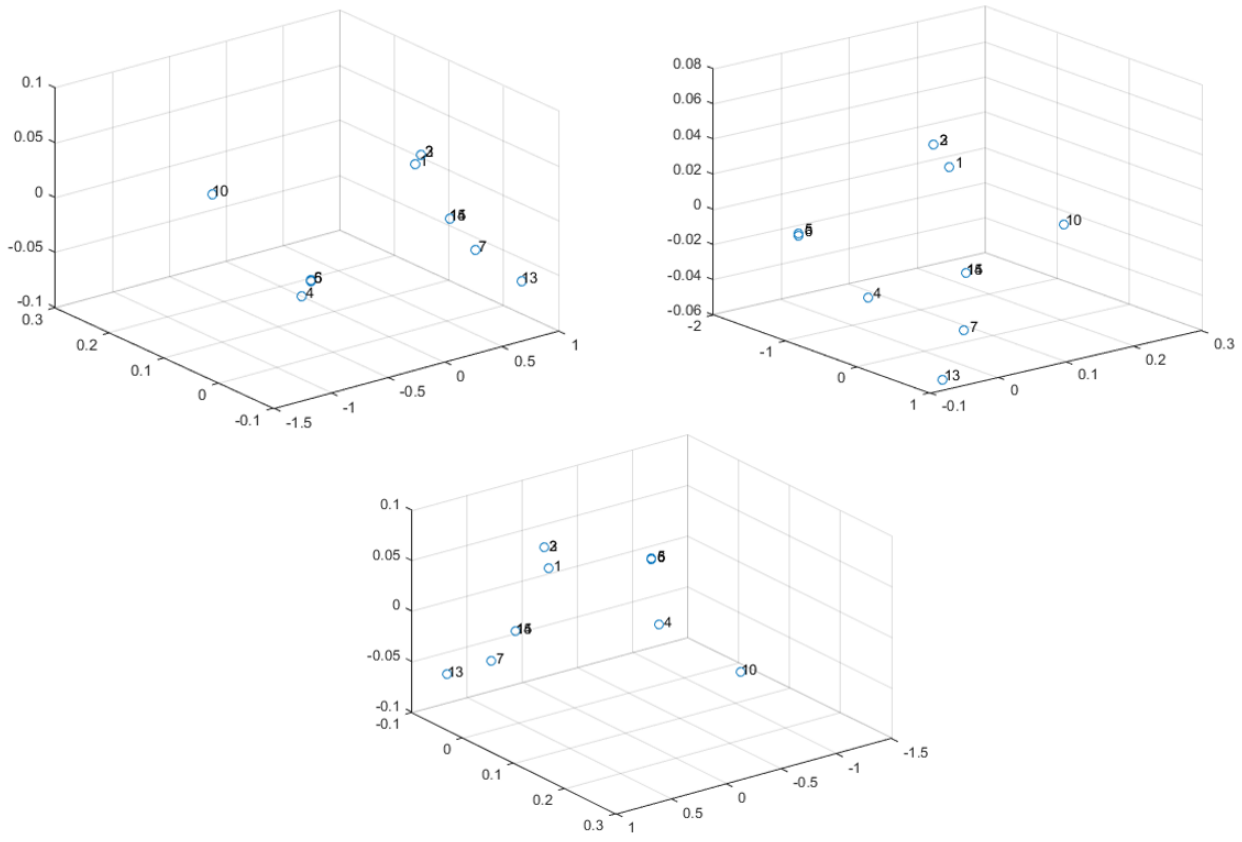

Figure 5.3: Views from different orientations of the same 3D representation for $\mathbf{B^{sp}}$ of the proximity matrix for all the RS OMs.

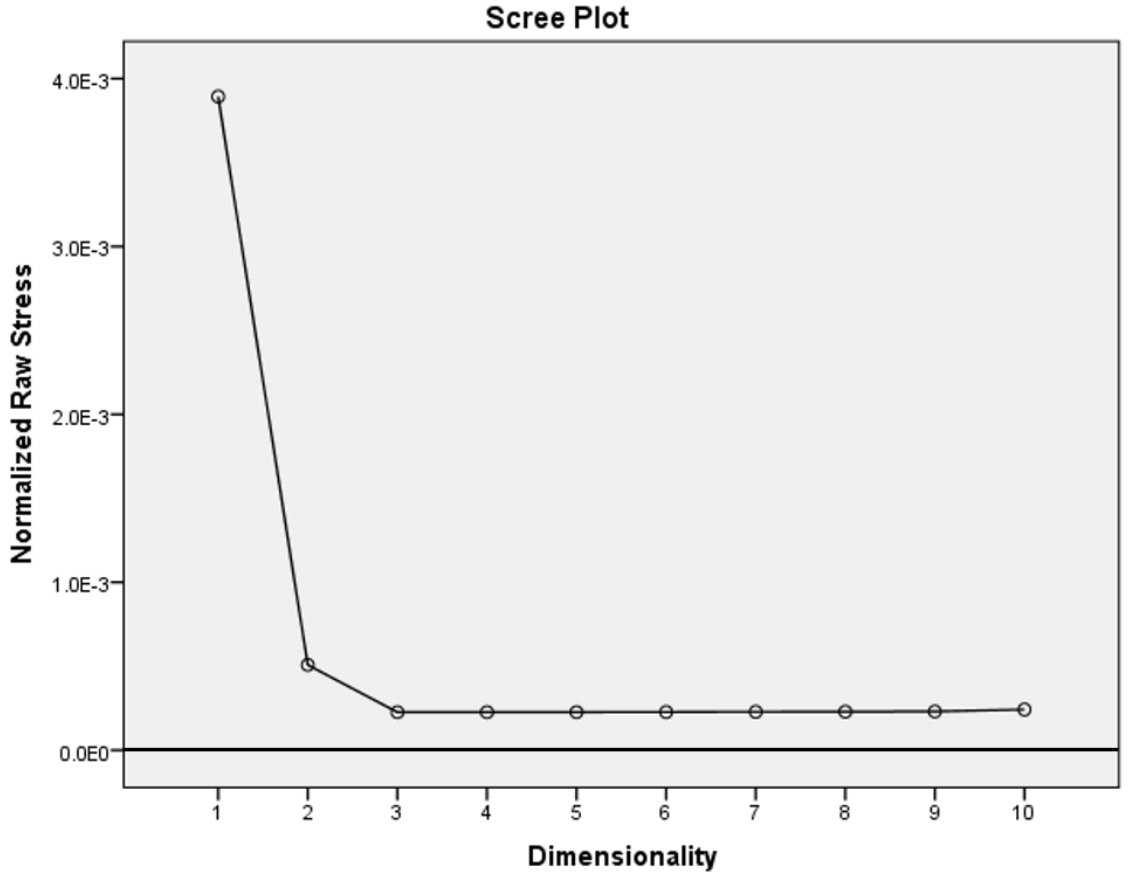

Figure 5.4: Scree plot for $\mathbf{N_{ya}}$ showing the normalised raw stress values.

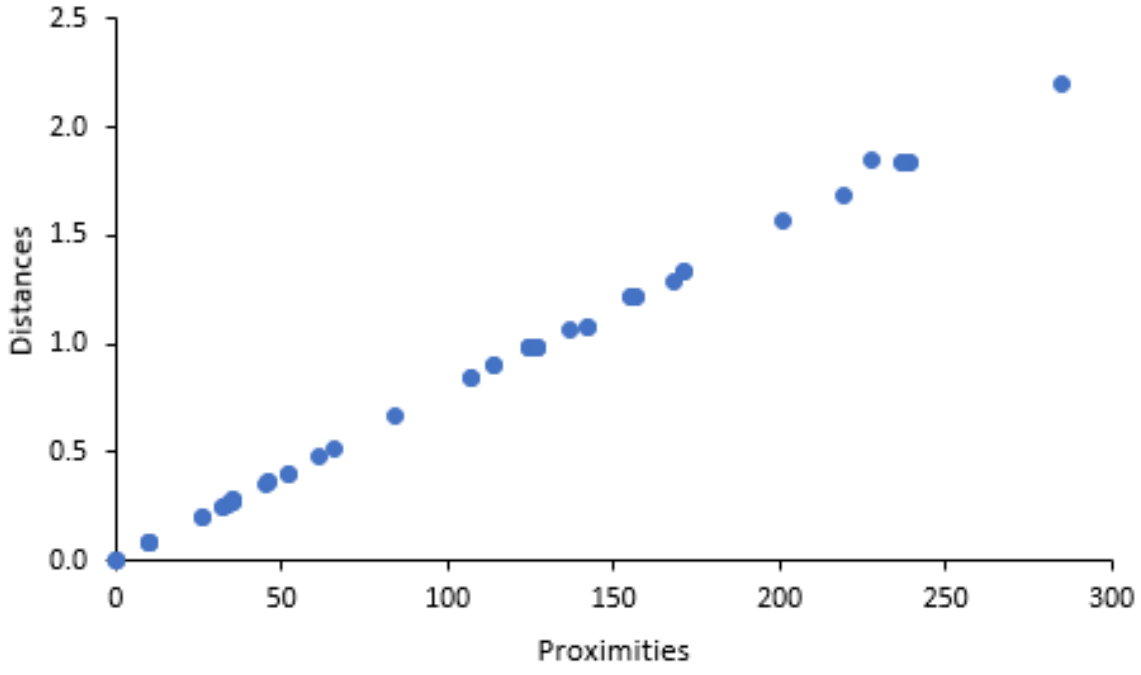

Figure 5.5: Shepard diagram for $\mathbf{N_{ya}}$ for a 3D representation.

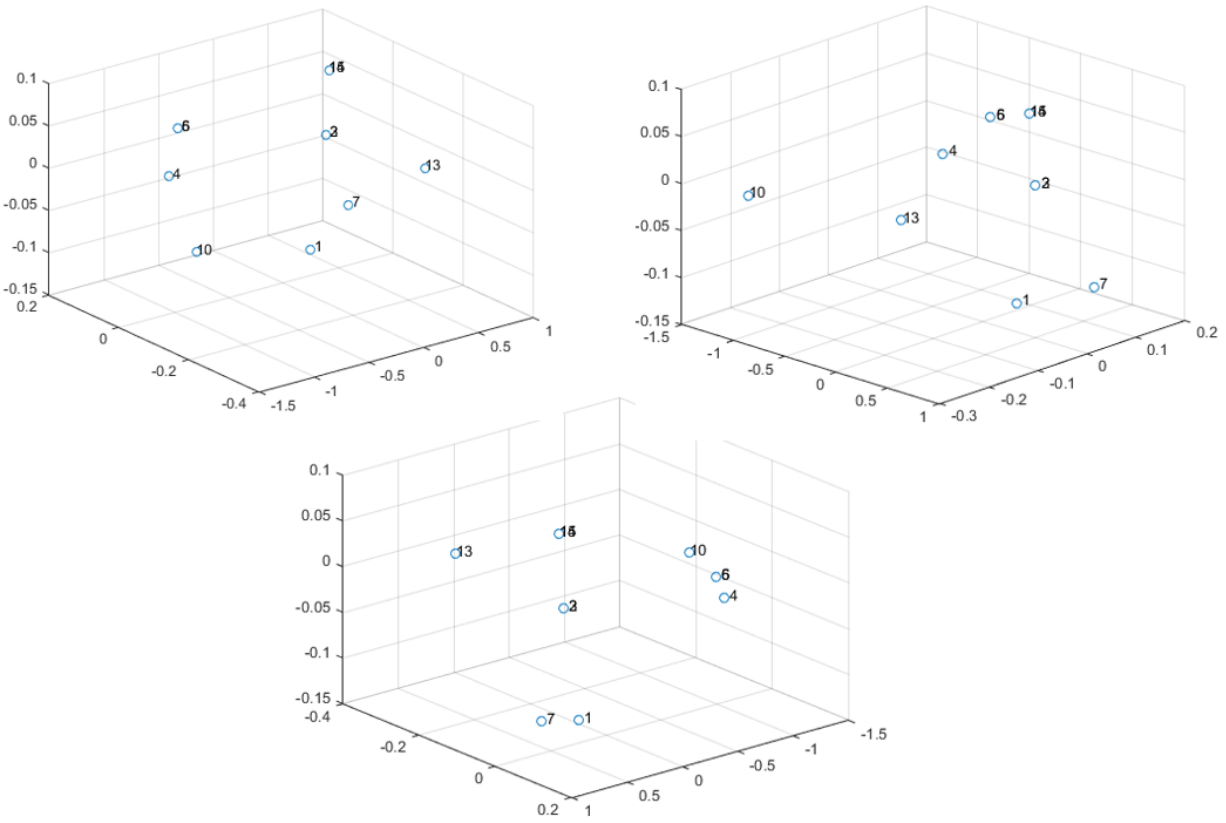

Figure 5.6: Views from different orientations of the same 3D representation for $\mathbf{N_{ya}}$ of the proximity matrix for all the RS OMs.

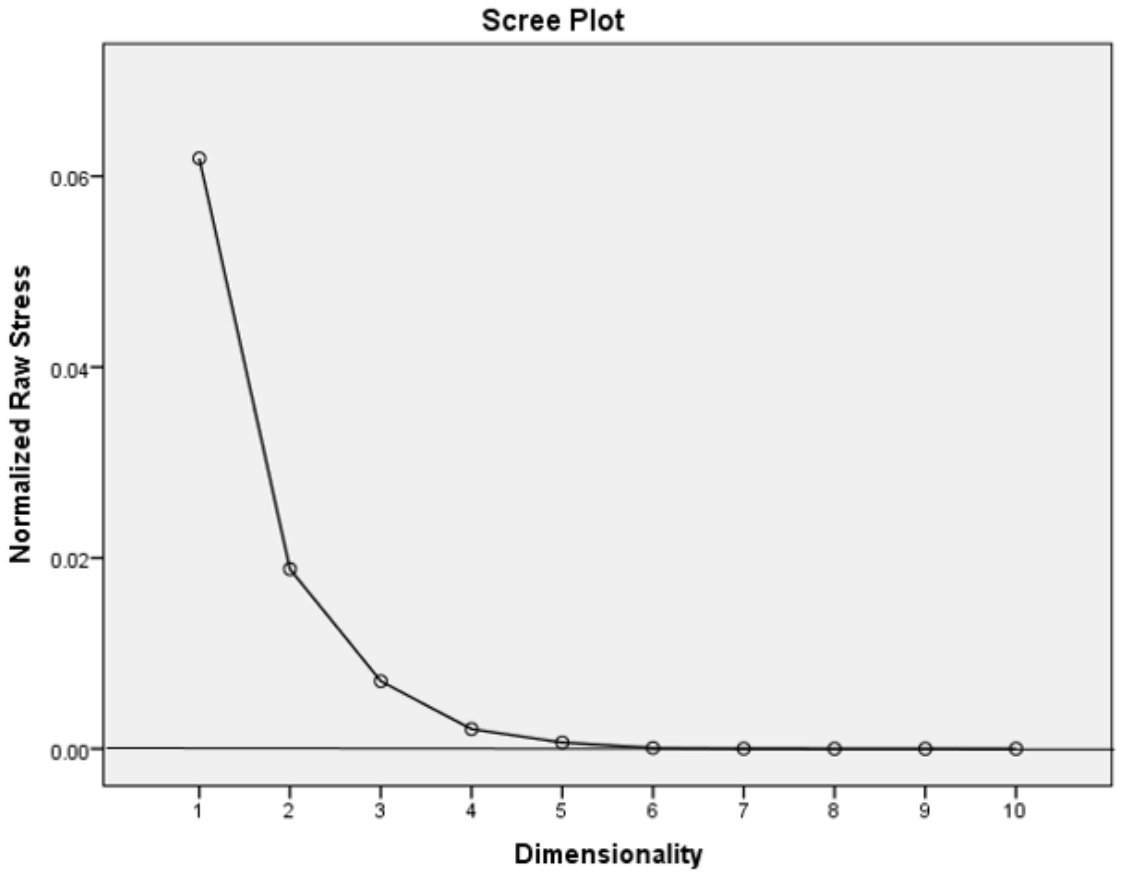

Figure 5.7: Scree plot for **CPUE** showing the normalised raw stress values.

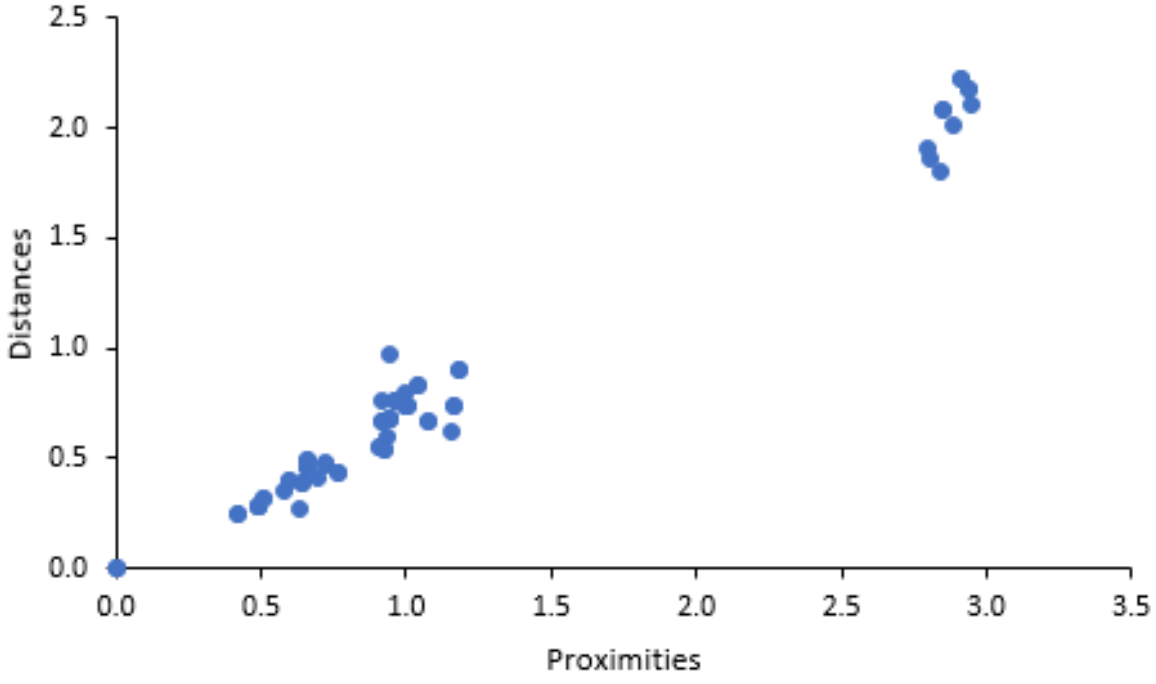

Figure 5.8: Shepard diagram for **CPUE** for a 3D representation.

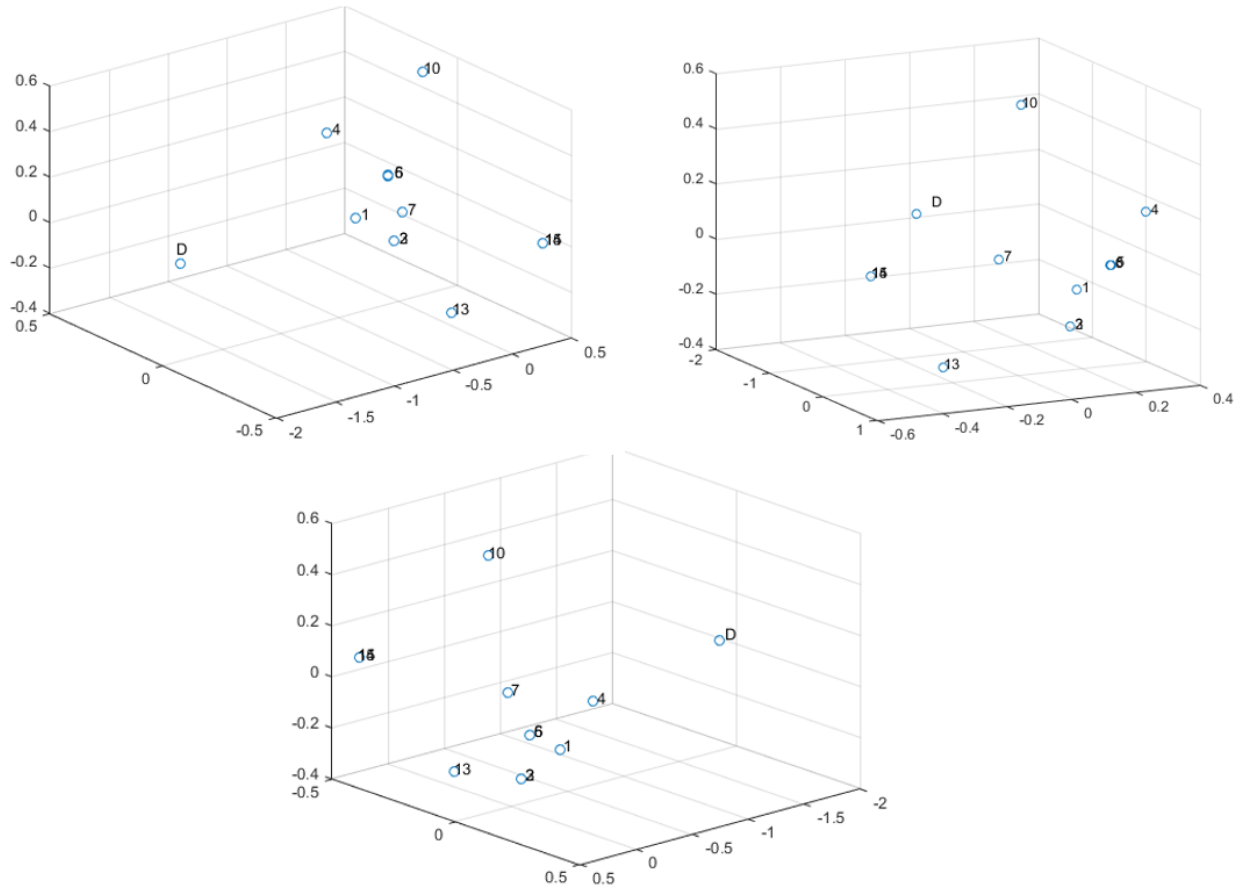

Figure 5.9: Views from different orientations of the same 3D representation for **CPUE** of the proximity matrix for all the RS OMs as well as the data which is shown as "D".

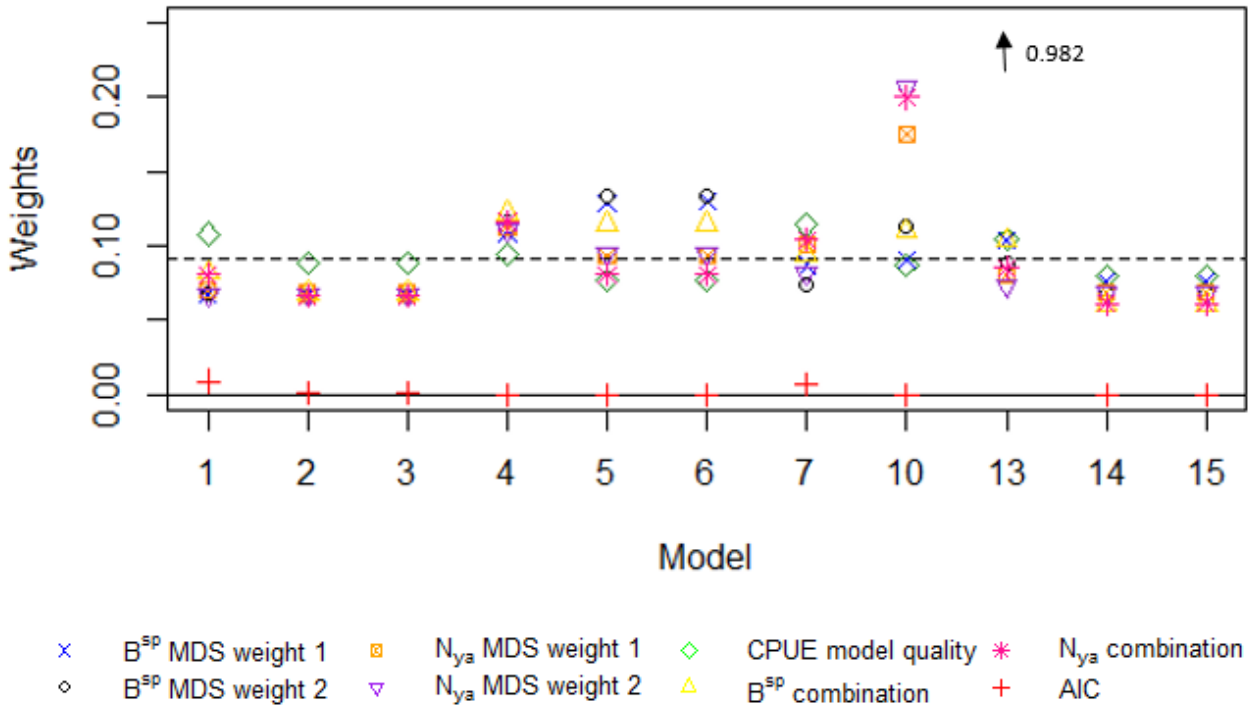

Figure 5.10: Model weights determined using the five different methods - B^{sp} MDS weight (1) (blue x), B^{sp} MDS weight (2) (black circle), N_{ya} MDS weight (1) (orange x-box), N_{ya} MDS weight (2) (purple downward facing triangle), CPUE model quality weight (green diamond), B^{sp} combination (yellow upward facing triangle), N_{ya} combination (pink star) and AIC weights (red cross). The arrow indicates an AIC weight of value 0.982 for RS13.

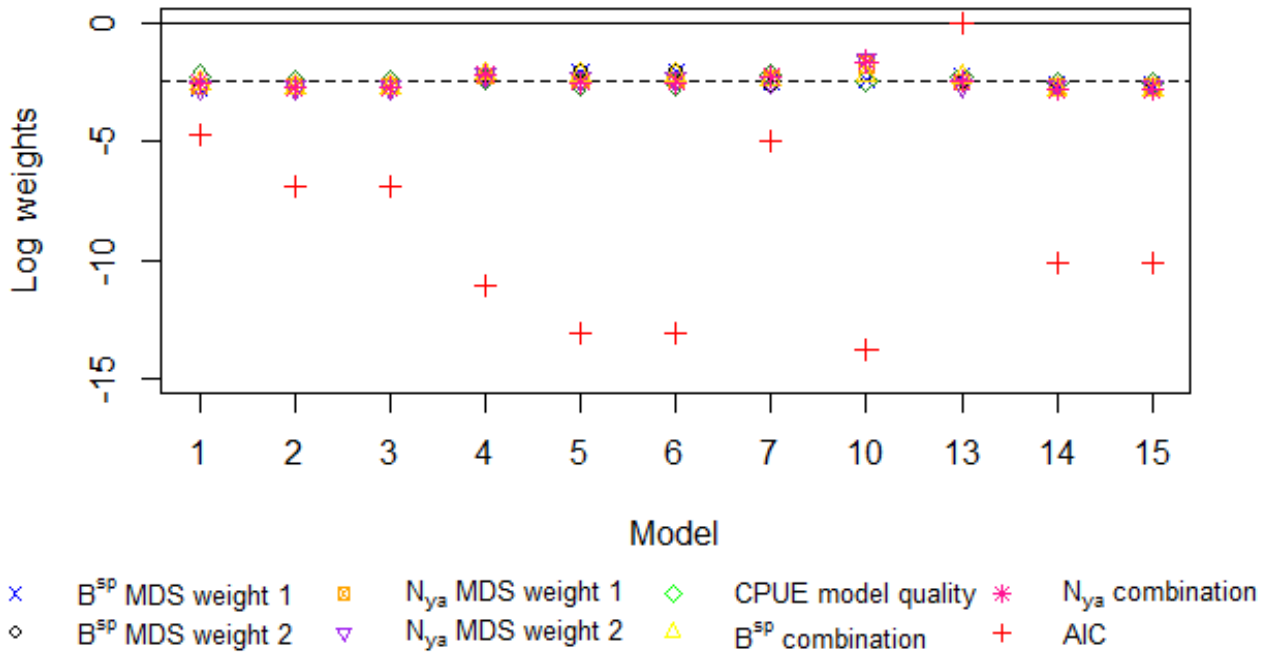

Figure 5.11: Log values of model weights determined using the five different methods - B^{sp} MDS weight (1) (blue x), B^{sp} MDS weight (2) (black circle), N_{ya} MDS weight (1) (orange x-box), N_{ya} MDS weight (2) (purple downward facing triangle), CPUE model quality weight (green diamond), B^{sp} combination (yellow upward facing triangle), N_{ya} combination (pink star) and AIC weights (red cross).

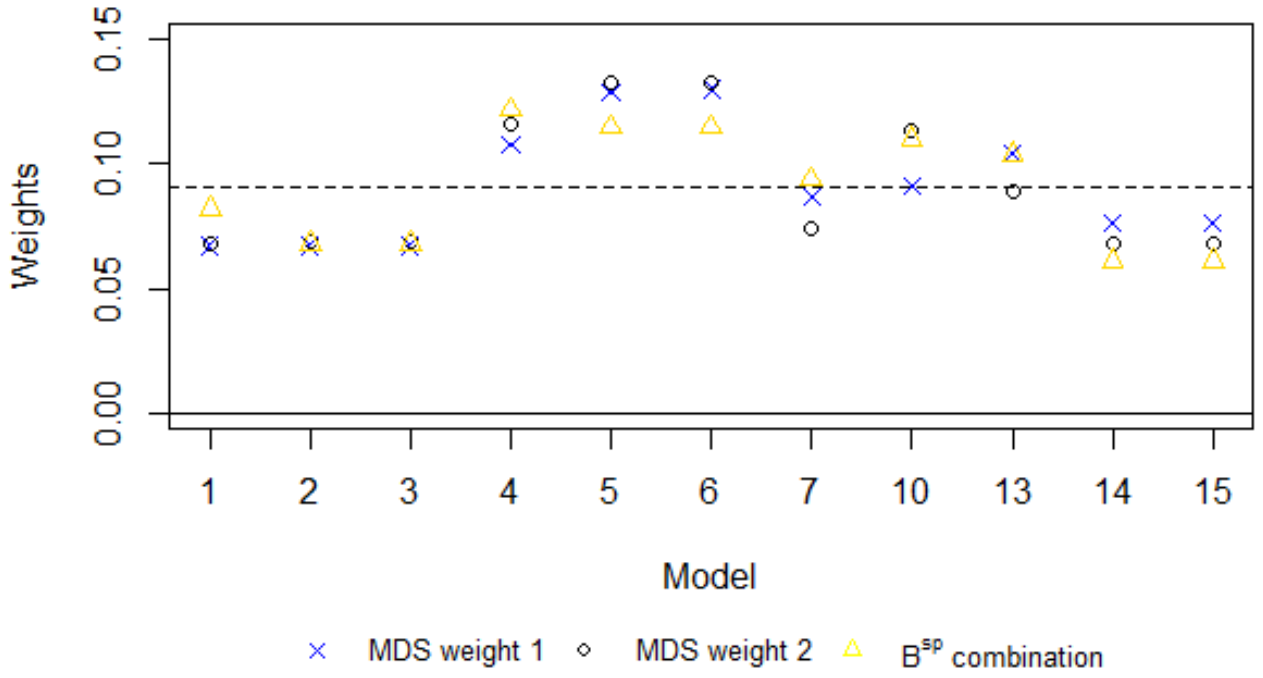

Figure 5.12: B^{sp} weights: MDS weight (1) (blue x), MDS weight (2) (black circle) and B^{sp} combination (yellow triangle).

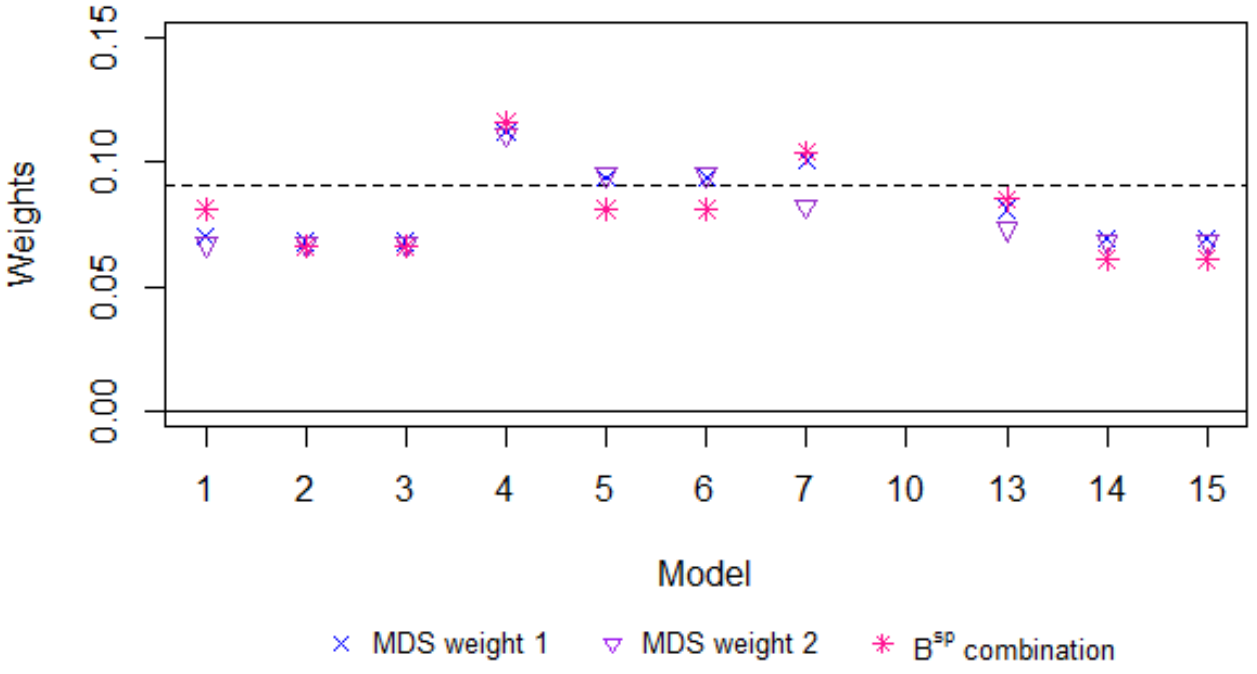

Figure 5.13: N_{ya} weights: MDS weight (1) (blue x), MDS weight (2) (purple triangle) and B^{sp} combination (pink star).

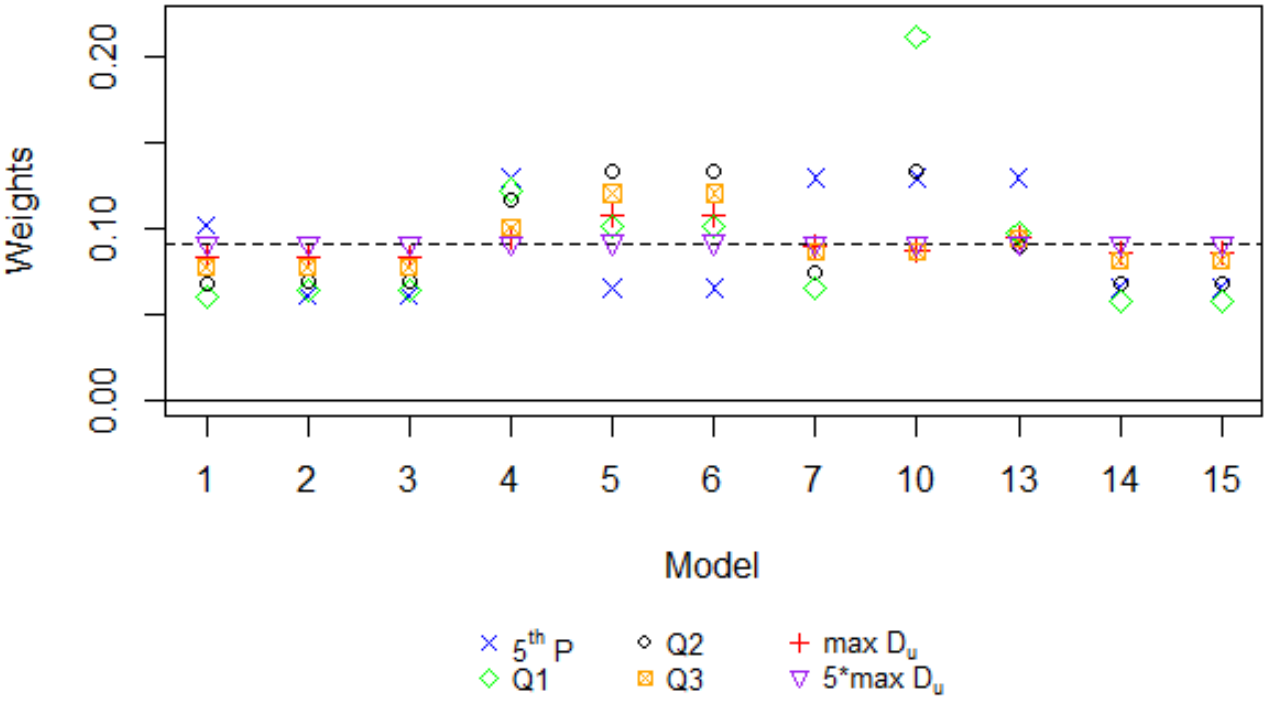

Figure 5.14: Sensitivity to the D_u value choice: **B^{sp} MDS weights (2)** with 5^{th} P (blue x), Q1 (green diamond), Q2 (black circle), Q3 (orange square), maximum (red cross) and five times the maximum (purple triangle) values of D_u.

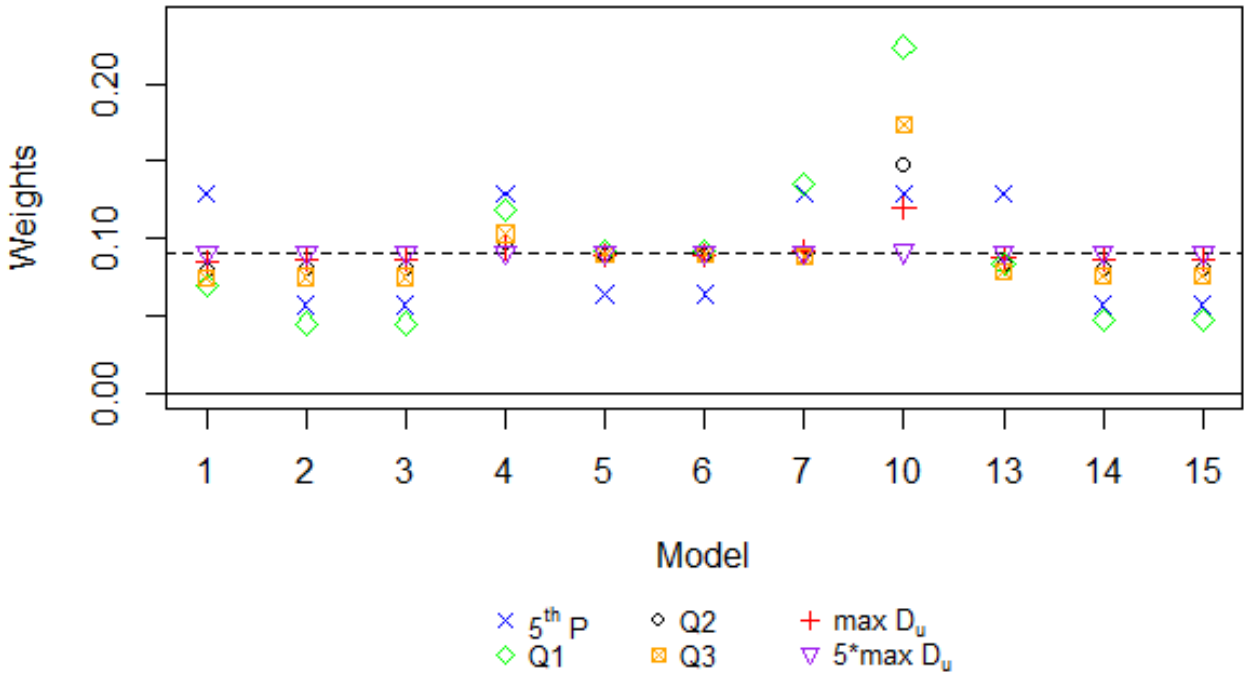

Figure 5.15: Sensitivity to the D_u value choice: $\mathbf{N_{ya}}$ **MDS weights (2)** with 5^{th} P (blue x), Q1 (green diamond), Q2 (black circle), Q3 (orange square), maximum (red cross) and five times the maximum (purple triangle) values of D_u.

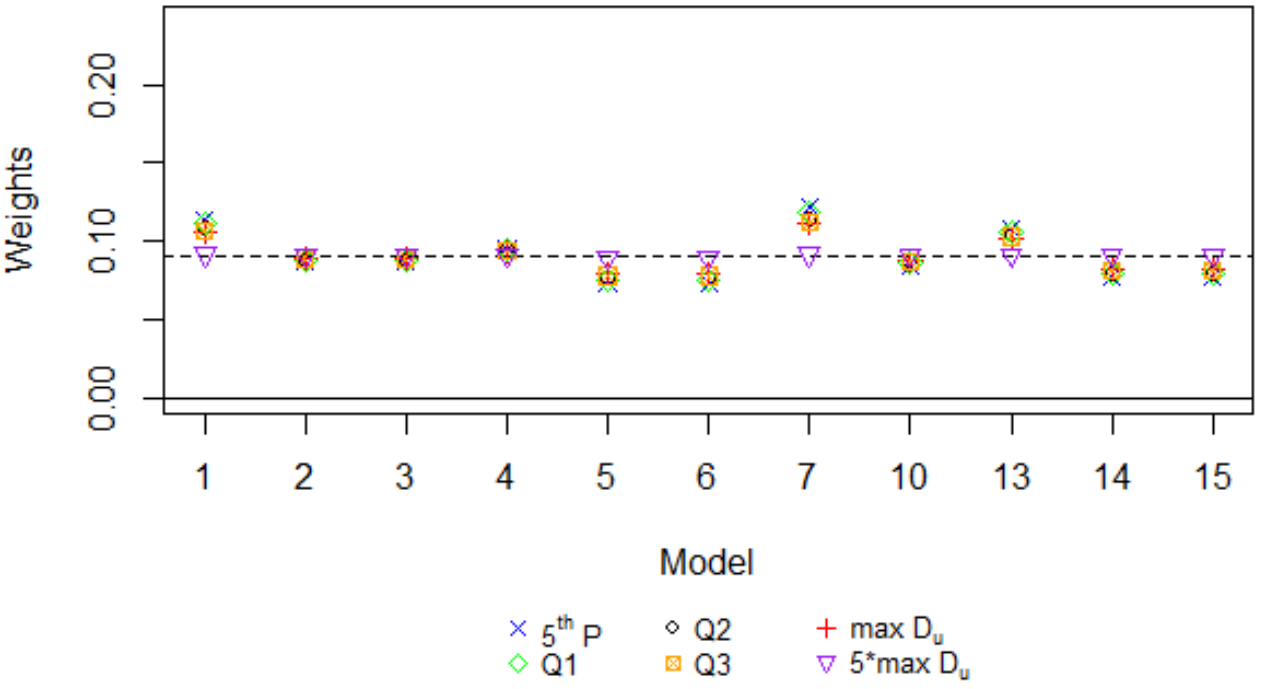

Figure 5.16: Sensitivity to the D_q value choice: **CPUE model quality weights** with 5^{th} P (blue x), Q1 (green diamond), Q2 (black circle), Q3 (orange square), maximum (red cross) and five times the maximum (purple triangle) values of D_q.

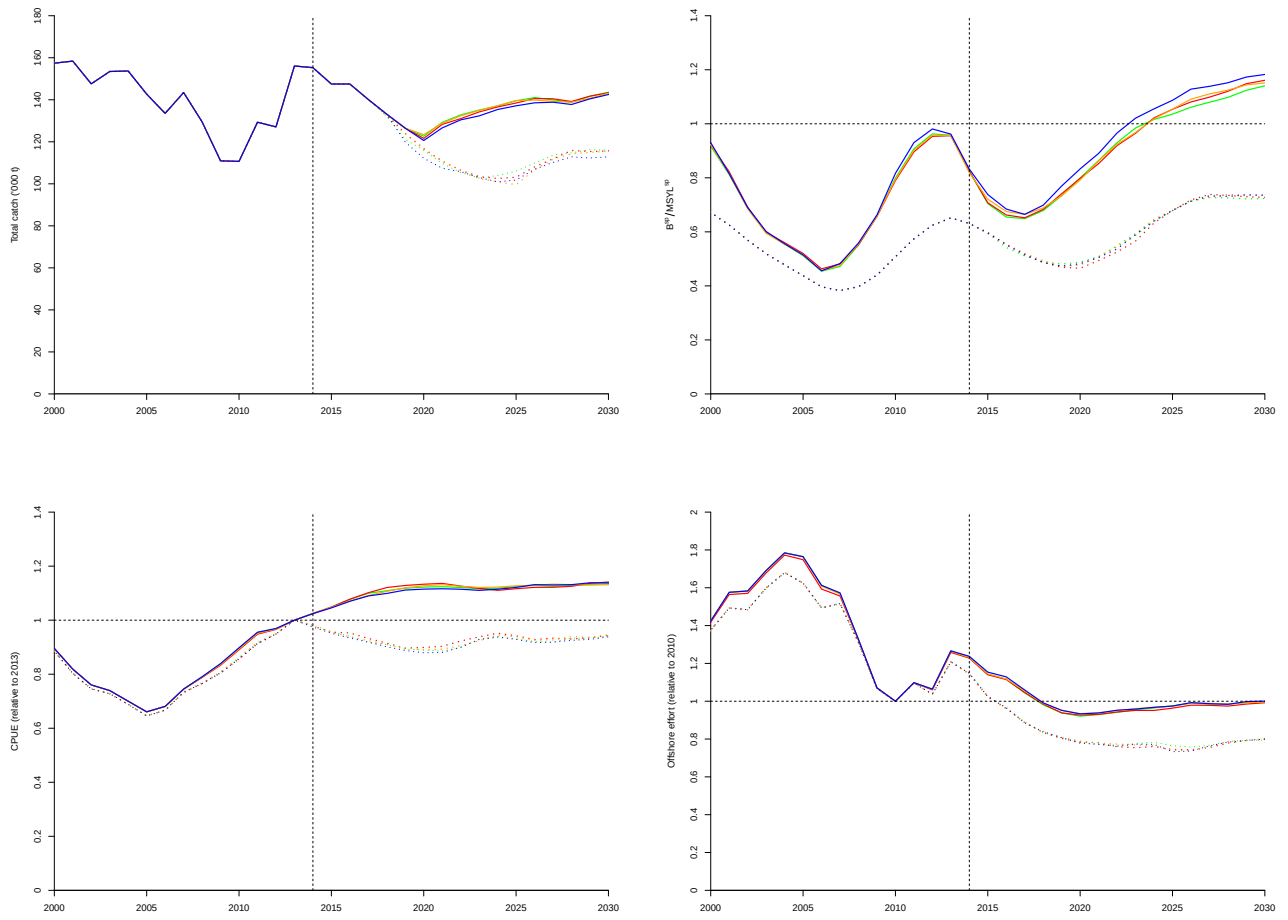

Figure 5.17: Projection weighting using $\mathbf{B^{sp}}$ estimates. Medians (full lines) and lower 5%iles (dotted lines) for total catch (top row, LHS), *M. paradoxus* spawning biomass (relative to MSYL – top row, RHS), CPUE (relative to the 2013 value, bottom row LHS) and effort (relative to the 2010 value, bottom row, RHS) for the RS with each OM equally weighted (blue) and with OMs unequally weighted – using MDS weight (1) (green), MDS weight (2) (red) and the combination weights (orange) - with a horizontal dashed line at 1 and a vertical dashed line at year 2014 when the future projections begin.

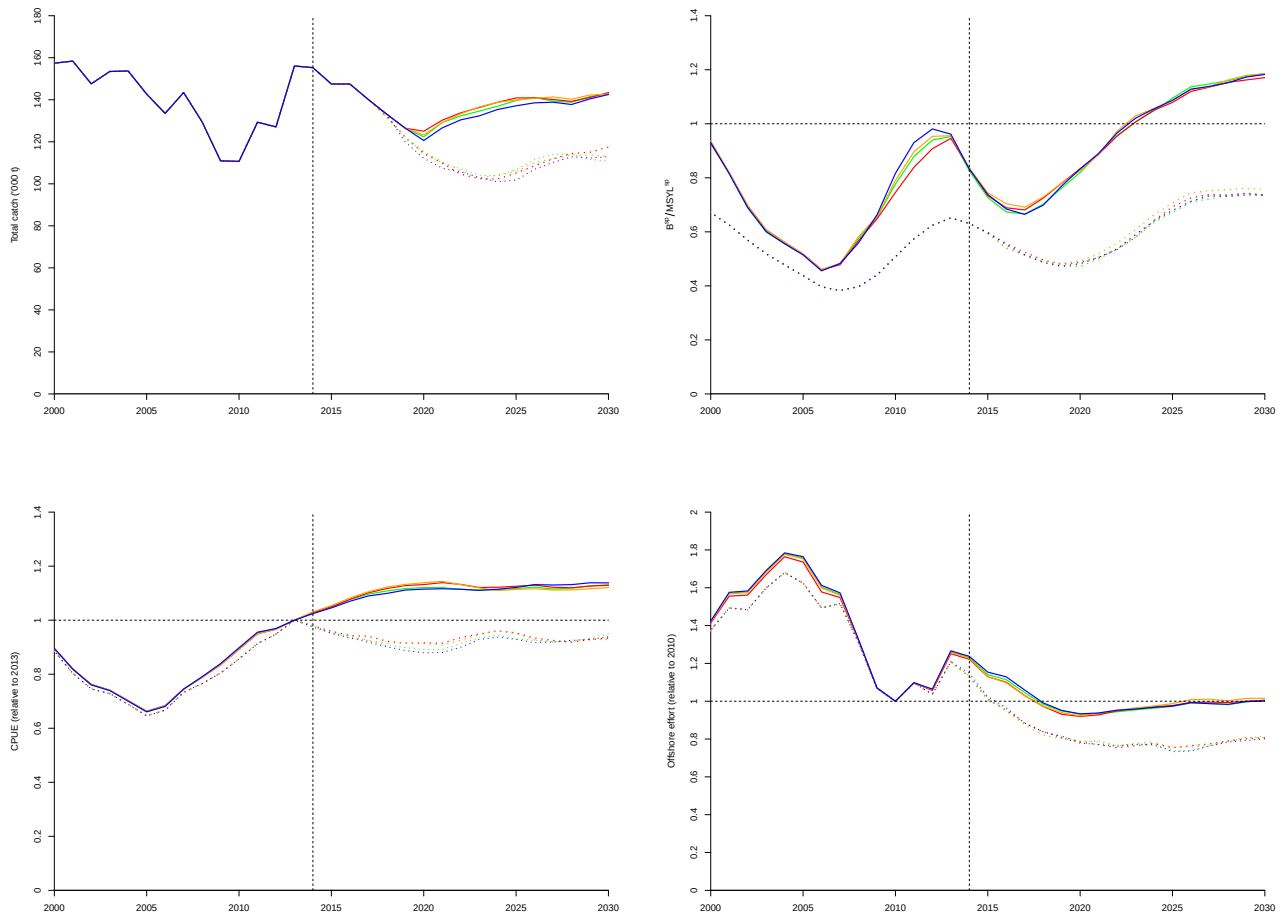

Figure 5.18: Projection weighting using $\mathbf{N_{ya}}$ estimates. Medians (full lines) and lower 5%iles (dotted lines) for total catch (top row, LHS), *M. paradoxus* spawning biomass (relative to MSYL – top row, RHS), CPUE (relative to the 2013 value, bottom row LHS) and effort (relative to the 2010 value, bottom row, RHS) for the RS with each OM equally weighted (blue) and with OMs unequally weighted – using MDS weight (1) (green), MDS weight (2) (red) and the combination weights (orange) - with a horizontal dashed line at 1 and a vertical dashed line at year 2014 when the future projections begin.

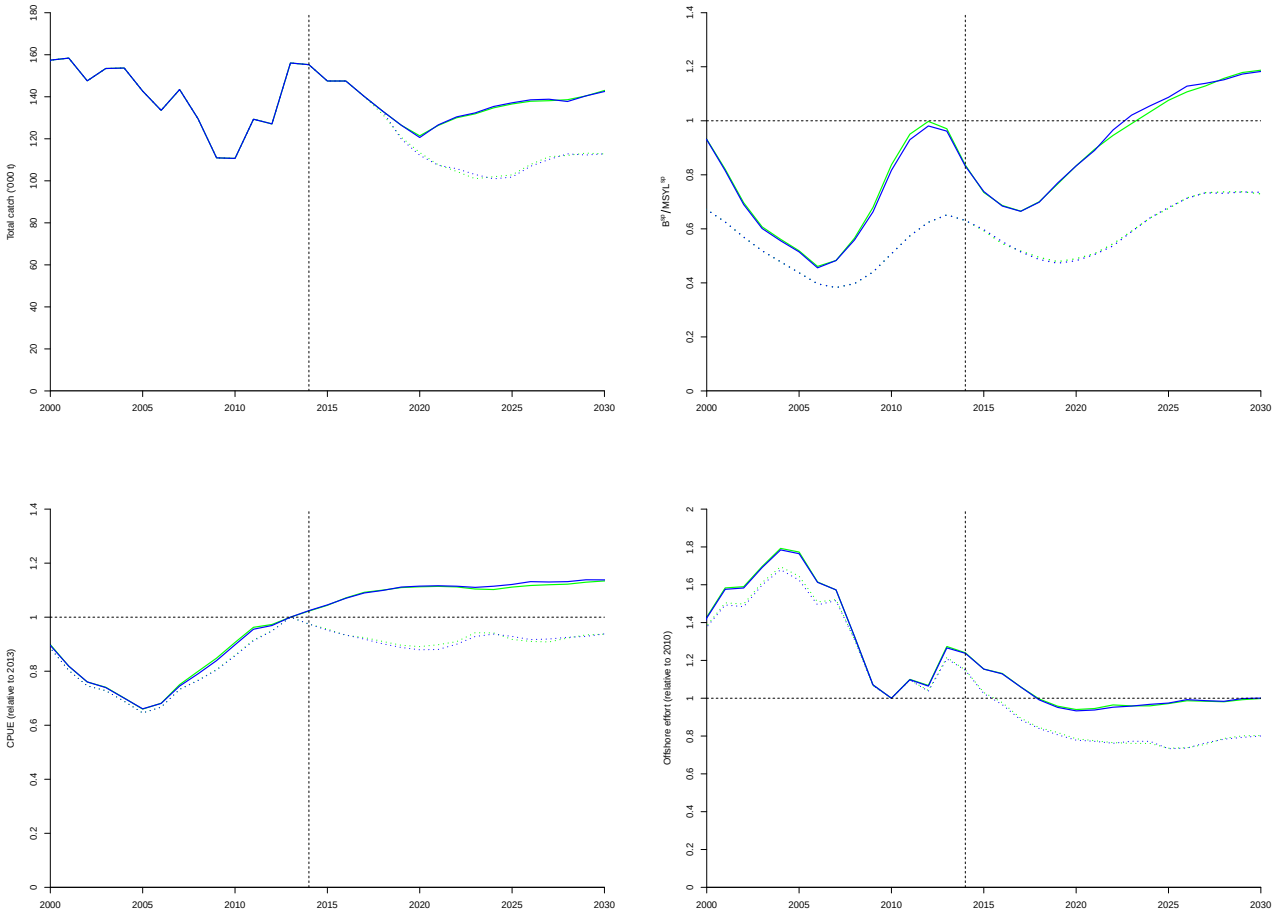

Figure 5.19: Projection weighting using **CPUE data and OM estimates.** Medians (full lines) and lower 5%iles (dotted lines) for total catch (top row, LHS), *M. paradoxus* spawning biomass (relative to MSYL – top row, RHS), CPUE (relative to the 2013 value, bottom row LHS) and effort (relative to the 2010 value, bottom row, RHS) for the RS with each OM equally weighted (blue) and with OMs unequally weighted using CPUE model quality weights (green) - with a horizontal dashed line at 1 and a vertical dashed line at year 2014 when the future projections begin.

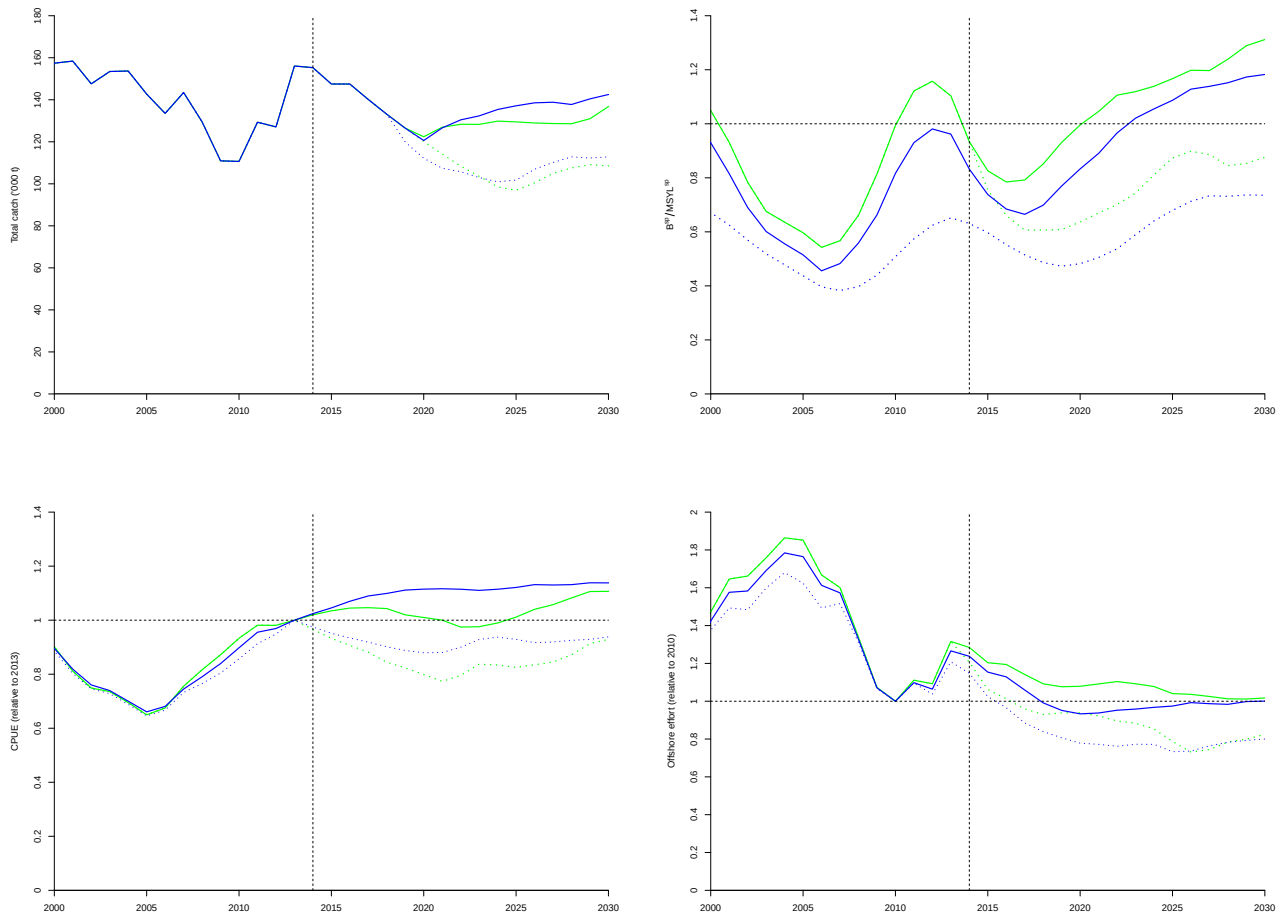

Figure 5.20: Projection weighting using **AIC** weights. Medians (full lines) and lower 5%iles (dotted lines) for total catch (top row, LHS), *M. paradoxus* spawning biomass (relative to MSYL – top row, RHS), CPUE (relative to 2013, bottom row LHS) and effort (relative to 2010, bottom row, RHS) for the RS with each OM equally weighted (blue) and with OMs unequally weighted using AIC weights (green) - with a horizontal dashed line at 1 and a vertical dashed line at year 2014 when the future projections begin.

Chapter 6

Conclusion and Future work

Fisheries management has a long history, having started gradually in the middle of the 19th century. As the awareness of the importance of managing fisheries increased, the need for fisheries scientists and for methodical research into the dynamics of fish populations arose. The methods and science used to manage fisheries have continued to grow and improve since then. Discussions around climate change have been ongoing for a long time, resulting in the field of climate change science which focuses on the various components of the natural environment. Both fisheries management and climate change science have similar main objectives and overall methods for achieving those objectives. Those similarities have been illustrated by using the example of the South African hake fishery where, as in other fisheries, problems can occur when an equally weighted average over models is used. In order to address these problems, it is worthwhile investigating whether one or more methods used in climate change to address similar problems can be applied in the case of the hake fishery. For this study, the aim was to determine the impact that the use of the model ensemble approaches used in climate change would have had on the current results obtained from the use of an equally weighted model ensemble in developing and selecting a management procedure for the South African hake resource.

The investigation of uncertainties, model ensembles and how the models in the ensembles are weighted in both fisheries management and climate change, which was detailed in Chapter 2, showed that there are both similarities and differences among these three aspects in both fields. As expected, when it comes to model structure, both fields are subject to uncertainty regarding initial condition assumptions, how to parameterise the model and the values of the parameters. Even though there is rather more internal variability in climate systems than in fisheries, both fields must simplify their systems in order to model them, which leads to uncertainty. Implementation error in fisheries and scenario uncertainty in climate sciences are similar types of uncertainty related to future scenarios. Observation error occurs in some way whenever data are collected, but is a more important consideration in fisheries than in climate change, owing to the generally greater difficulties and expense of collecting data, for the former.

In addition, it was shown that there is a common type of model ensemble used in both fisheries and climate change fields: the multimodel ensemble (MME). Although the models that make up the ensembles are different, the idea of determining the skill of a model (its ability to replicate processes for which there are observations) is common between the fields. Both fields use Bayesian methods or weighted averages in order to integrate results aggregated over the individual models in MMEs. Models in an ensemble are, however, not fully independent. This is the case in both fisheries management and climate change. In climate science, this problem has, in some cases, been addressed by determining how "near" models are to one another and downweighting the models

that are more similar. Essentially, an attempt is made to find an "unbiased" average by downweighting similar "nearer" models. The concept of weighting in relation to model "nearness" has not been considered extensively in fisheries, so that the application of this method is investigated using the South African hake resource as an example. The climate change methods used (Sanderson *et al.* 2015a) are described in more detail in Chapter 4.

Following Chapter 3, which summarised the history of the South African hake fishery and detailed the OMP used to manage it, Chapter 4 focussed on the data and methods used. Three different input types were used (spawning biomass, numbers-at-age and CPUE) to compare and find weights for the individual OMs in the RS. Proximity matrices for each data type were calculated, and used as input to a multidimensional scaling (MDS) algorithm which allowed the proximities to be represented in a low-dimensional space. These proximities provided the input for four of the five different weighting methods used to provide weights for each of the OMs in the RS. Three of the weighting methods were taken from climate change (Sanderson *et al.* 2015a), while the others were simple, more generalised methods. The resultant weights were then used in Chapter 5 to integrate over these OMs when projecting Catch, $B^{sp}/MSYL^{sp}$, CPUE and Effort forward under OMP-2014.

Chapter 5 presented and discussed the results of the main analyses and methods. More specifically, it provided and analysed the results of the MDS analyses, the different weights for each of the RS OMs (obtained using the weighting methods), and projections using the weighted RS with OMP-2014.

Findings

The multidimensional scaling method used to represent the models in the RS in a lower dimension was found to be sufficient as a visualisation tool for the purposes of this dissertation. When attempting to represent the B^{sp} and N_{ya} inputs, the stress values were low, but were higher for the CPUE case. When comparing the outputs of each model to those of the other models (using MDS), it was found that RS4, RS5, RS6 and RS10 were the "furthest away" from (i.e. most dis-similar to) the other OMs. When comparing the model output to the observed (CPUE) data (again using MDS), i.e. model fits to the data, RS5, RS6, RS10, RS14 and RS15 were the "furthest" from the data, essentially because they did not fit the data as well as the other models.

The different weighting methods each produced different weights for the OMs. The model uniqueness MDS weights were relatively similar for both B^{sp} and N_{ya} inputs, and the weights reflected the "nearness" shown using MDS. The model quality (CPUE data) and AIC weights were considerably different from the uniqueness weights and from each other. This is because the model fit was only considered for one component of the available information (CPUE) for the model quality weights, but the AIC weights are based on the log-likelihood values for each of the models which show the fit of the OMs to all the data and indicate that RS13 fits the data well, with the other models fitting the data somewhat poorly in comparison. The AIC weighting method is not recommended[7], but is included here as an illustration and to allow a comparison with the other weighting schemes. In order to consider both model similarity and the goodness of fit of the model, a combination weight was used.

For the Sanderson *et al.* (2015a) model uniqueness and model quality weight methods, an investigation was conducted into the sensitivity of the weights to the value of one parameter of the weighting function, the "radius of similarity". The OM pairs that are separated by less than the parameter value are considered to be similar. It was found that the weights were quite sensitive to the value if this parameter. The median of the Euclidean distances between the models was ultimately used to determine the OM weights because this is in essence the

[7]The reason is that the data to which the models are fit may not satisfy the assumptions underlying AIC-weights, such as independence of these data.

same approach as that in Sanderson *et al.* (2015a), and because it allows for a reasonably wide range of weights which helps to visualise the way in which this weighting method works. Although it is difficult to know which value for the parameter is the most appropriate, the presence of this parameter does allow for flexibility when deciding what amount of similarity between models is acceptable.

When using the weights produced from the B^{sp} estimates, the weighted RS provided a lower spawning biomass projection for *M. paradoxus* than the equally weighted RS that had been used to select the current hake OMP in 2014. This suggests that, had some unequal weighting approach been used in 2014, it might have led to the selection of a slightly more conservative OMP, which would have set catches lower. When using the weights produced from the N_{ya} estimates, the spawning biomass projections are very similar to the equally weighted RS, so that weighting on that basis would not have made much difference to the selection of the OMP. When using the CPUE model quality weights, the weighted RS provided a lower spawning biomass projection for *M. paradoxus* than the equally weighted RS used to select the current hake OMP in 2014. As is the case with the weights produced from the B^{sp} estimates, this approach might have led to the selection of a slightly more conservative OMP. The projection using the AIC weights provides (on average) a much higher spawning biomass projection for *M. paradoxus* than the equally weighted RS used to select the current hake OMP in 2014. If these weights had been used in 2014, a much less conservative OMP, allowing for more catches to be taken, would have been selected.

Certification of the hake trawl fishery by the Marine Stewardship Council is very important for the hake industry for economic reasons (Lallemand *et al.* 2016). Since the time taken for a resource below MSYL to recover to MSYL is important in this certification process, the impact of different weighting schemes for the RS is of interest in this context. Of all the unequally weighted approaches to averaging, the only one for which the spawning biomass for *M. paradoxus* is projected to reach MSYL sooner than the equally weighted average (two years earlier) is the AIC weighted projection. The others predict the population to reach MSYL at the same time or a year later than the equally weighted OMP-2014 projection. The difference in this time to reach MSYL arising from the different weighting approaches is therefore not substantial.

In summary, it seems that weighting the OMs in the RS for the South African hake fishery using the climate change model weighting methods illustrated here does not have a major impact on the results obtained from using the equally weighted model RS adopted in the development of the OMP-2014 for the resource. Although these climate change methods can be applied in this fisheries management context, the weights they produced did not add considerable value to the equally weighted average method used currently for South African hake. However, the object here was only to illustrate these approaches. It could well be that for other fisheries the weighting scheme could have a greater effect on the eventual results.

There still continues to be the question of how best to "average" across the two very different factors of model (dis-)similarity and of the goodness of fit of the model to the data. In this dissertation, the product of the model uniqueness weight (based on model (dis-)similarity) and the model quality weight (based on goodness of fit to the data) was used in order to take both features into account. This was a subjective method used by Sanderson *et al.* (2015a) and is not necessarily the most appropriate. Clearly, there must be some minimum criterion for achieving an adequate fit to the data, after which attention should be paid to the downweighting of similar models, but the "best" way to achieve this is still open for debate.

Future work

This section details future research that could further address some of the problems and answer some of the questions associated with this research.

Multidimensional scaling

A more detailed investigation of the stress values associated with the MDS process might prove interesting, in particular as to why the stress values were higher when using the CPUE input than when using the other two inputs. The costs and benefits of using 3D, or any of the other dimensions, to represent the proximities could be considered, along with the choice of inputs (B^{sp}, numbers-at-age and CPUE). The MDS process could also be repeated for a number of starting points and the results with the lowest stress value chosen since, as with many minimisations, there is no guarantee for what is an automated package procedure that a minimum has been reached. A number of different MDS setting combinations could also be considered, apart from the settings used here (see Appendix 4.B in Chapter 4). Other methods of determining (dis-similarity) between OMs as well as different ways of determining how well the OMs fit the data could be investigated. Further investigation could be conducted into weighting models using the presence-absence method and how it could be applied to this example. Random ensembles could be generated, as implemented by Sanderson *et al.* (2015a), in order to test how likely it is that the RS output was drawn from a set of independent models.

Weights

The justification for the values of the parameters in the Sanderson *et al.* (2015a) weighting methods could be investigated more thoroughly. The randomly generated ensembles could be used to define the values of these parameters. Sanderson *et al.* (2015a) defined the D_u parameter to be the 50th percentile of the nearest-neighbour distances in the 10^5 randomly generated ensembles. The form of the weight equations suggested by Sanderson *et al.* (2015a) could be investigated and possibly changed. Another option, instead of simply weighting each model, could be to remove interdependent models (almost) entirely. Sanderson *et al.* (2015a) propose a stepwise model elimination method, where the models with the highest co-dependencies are removed first. They propose a strategy that considers both model performance and model independence when creating an ensemble subset.

Different ways of combining the two aspects of model (dis-)similarity and the goodness of fit of the model need to be investigated. Research could also be conducted into other ensemble weighting methods used in climate change science or elsewhere. For example, in the companion paper, Sanderson *et al.* (2015b) propose a different way to account for model performance and interdependence. A method is proposed that produces probabilistic estimates that are largely insensitive to model duplicates and can consider model performance.

References

Aho, K., Derryberry, D. and Peterson, T. 2014. Model selection for ecologists: the worldviews of AIC and BIC. *Ecology*, **95**(3), 631–636.

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. *Pages 267–281 of:* Petrov, B.N. and Caski, S. (eds), *Second International Symposium on Information Theory, Budapest, Hungary.*

Allouche, O., Tsoar, A. and Kadmon, R. 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *Journal of Applied Ecology*, **43**(6), 1223–1232.

Anderson, R., Auerswald, L., Butterworth, D., Cockraft, A., Coetzee, J., da Silva, C., Durholtz, D., Fairweather, T., Geja, Y., Githaiga-Mwicigi, J., Kemp, D., Kerwath, S., Lamberth, S., Leslie, R., Mackenzie, A., Maharaj, G., Mbande, S., Prochazka, K., Rothman, M., Singh, L., Twatwa, N., van der Lingen, C. and West, W. 2014. Status of the South African Marine fishery resources. *Department of Agriculture, Forestry and Fisheries, South Africa Technical Report*, 1–77.

Anderson, S., Cooper, A., Jensen, O., Thorson, J., Walsh, J., Afflerbach, J., Dickey-Collas, M., Kleisner, K., Longo, C., Ovando, D., Mosqueira, I., Rosenberg, A. and Selig, E. 2017. Improving estimates of population status and trend with superensemble models. *Fish and Fisheries*, **18**(4), 732–741.

Andrew, P.A. and Butterworth, D.S. 1987. Is $f_{0.1}$ an appropriate harvesting strategy for the Cape hakes? *South African Journal of Marine Science*, **5**(1), 925–935.

Bolin, B. 2008. *A history of the science and politics of climate change: the role of the Intergovernmental Panel on climate change.* Cambridge University Press, 1–292.

Borg, I. and Groenen, P.J.F. 2005. MDS models and measures of fit. *Chap. 3, pages 37–61 of: Modern Multidimensional Scaling: theory and applications*, 2 edn. New York, USA: Springer Science+Business Media, Inc.

Breen, P.A. 2015. *Operational management procedures for New Zealand rock lobster stocks (Jasus edwardsii) in 2015.* Tech. rept. September. Ministry for Primary Industries, New Zealand, 1–27.

Butterworth, Doug S. 2007. Why a management procedure approach? Some positive and negatives. *ICES Journal of Marine Science*, **64**, 613–617.

Butterworth, D.S. 2010. An Overview of MSE: Management strategy evaluation alternatively termed the Management Procedure Approach. *PowerPoint Presentation. Canadian/Apr/2010*, 97.

Butterworth, D.S. and Andrew, P.A. 1984. Dynamic catch-effort models for the hake stocks in ICSEAF Divisions 1.3–2.2. *Collection of Scientific Papers of the International Commission for the Southeast Atlantic Fisheries*, **11**(1), 29–58.

Butterworth, D.S. and Rademeyer, R.A. 2005. Sustainable management initiatives for the Southern African hake fisheries over recent years. *Bulletin of Marine Science*, **76**(2), 287–319.

Chalmers, D.S. 1976. Weight conversion factors, length/weight relationships and annual landings of some South African trawl-caught fish. *Fisheries Bulletin: Contributions to Oceanography and Fisheries Biology*, **8**, 1–4.

Chandler, R.E. 2013. Exploiting strength, discounting weakness: combining information from multiple climate simulators. *Philosophical Transactions Royal Society A*, **371**(1991), 1–19.

Claeskens, G., Hjort, N.L., Shen, X., Dougherty, D.P., Johnson, W.O., Ishwaran, H., Rao, J.S., Cook, R.D., Li, L., Tsai, C., Raftery, A.E. and Zheng, Y. 2003. The Focused Information Criterion. *Journal of the American Statistical Association*, **98**(464), 900–945.

Cole, J.D. 1988. Some Observations on the Statutory Adoption in the Sea Fishery Act 1988 of the Diemont Commission's Recommendations and Comments Regarding the TAC and Quota Board. *Sea Changes: The Developing Regime of the Sea in Law and in State Practice*, 47–59.

Commandeur, J.J.F. and Heiser, W.J. 1993. Mathematical derivations in the proximity scaling (PROXSCAL) of symmetric data matrices. *Leiden, The Netherlands: Department of Data Theory, Leiden University Technical Report RR-93-03*, 1–60.

Cox, S., Howell, D. and Punt, A.E. 2017. International review panel report for the 2017 International Fisheries Stock Assessment Workshop. *Unpublished report*, 1–14.

Cox, S.P., Benson, A. and den Heyer, C.E. 2016. Framework for the assessment of Atlantic Halibut stocks on Scotian Shelf and Southern Grand Banks. *DFO Canadian Science Advisory Secretariat Research Document 2016/001*, 1–62.

Cunen, C., Walløe, L. and Hjort, N.L. 2017. Decline in energy storage in Antarctic minke whales during the JARPA period: Assessment via the Focused Information Criterion (FIC). *International Whaling Commission Technical Report SC/67A/EM/04*, 1–56.

De Jongh, J.G. 1974. *Ontwikkeling van die seevisserye aan die Kaapkolonie.* BAHons thesis, University of Cape Town.

Department of Environmental Affairs. 1988. *Sea Fishery Act.* Government Printer, Pretoria, South Africa.

Diemont, M.A., Barrie, F.G., Stoops, W.A., Ramsay, R. and Goldschmidt, E.H.B. 1986. Diemont Commission: Report of the Commission of Inquiry into the allocation of quotas for the exploitation of living marine resources. *Diemont Commission report, Government Printer, Pretoria, South Africa.*

Du Plessis, C.G., Botma, M.C., Du Toit, C.A., Hare, V., Lochner, J.P.A., Stander, R., Bosman, C.S. and Van Niekerk, P. van R. 1971. Du Plessis Commission: Report of the Commission of Inquiry into the fishing industry. The utilisation of the fish and other living marine resources of South Africa and South West Africa. *Du Plessis Commission report, Government Printer, Pretoria, South Africa.*

Durholtz, M.D., Singh, L., Fairweather, T.P., Leslie, R.W., van der Lingen, C.D., Bross, C.A.R., Hutchings, L., Rademeyer, R.A., Butterworth, D.S. and Payne, A.I.L. 2015. Fisheries, ecology and markets of South African hake. *Chap. 2, pages 38–69 of:* Arancibia, Ugo (ed), *Fish and Aquatic Resources Series 17: Hakes Biology and Exploitation.* John Wiley & Sons, Ltd, Chichester, UK.

Eyring, V., Bony, S., Meehl, G.A., Senior, C.A., Stevens, B., Stouffer, R.J. and Taylor, K.E. 2016. Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, **9**, 1937–1958.

Fairweather, T. 2012. Research survey hake data - 2012 update. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa DAFF/2012/OCT/SWG-DEM/20.*

FAO. 2016. The State of World Fisheries and Aquaculture 2016. Contributing to food security and nutrition for all. *Food and Agricultural Organisation of the United Nations, Rome*, 1–200.

Farmer, G.T. and Cook, J. 2013. *Climate change science: a modern synthesis: Volume 1-the physical climate.* Springer Science & Business Media, 1–444. [Accessed via Google books].

Fawcett, T. 2006. An introduction to ROC analysis. *Pattern Recognition Letters*, **27**(8), 861–874.

Fleming, J.R. 2005. *Historical perspectives on climate change.* Oxford University Press, 1–208. [Accessed via Google books].

Fournier, D.A., Skaug, H.J., Ancheta, J., Ianelli, J., Magnusson, A., Maunder, M.N., Nielsen, A. and Sibert, J. 2012. AD Model Builder: using automatic differentiation for statistical inference of highly parameterized complex nonlinear models. *Optimization Methods and Software*, **27**(2), 233–249.

Gardmark, A., Lindegren, M., Neuenfeldt, S., Blenckner, T., Heikinheimo, O., Muller-Karulis, B., Niiranen, S., Tomczak, M.T., Aro, E., Wikstrom, A. and Mollman, C. 2013. Biological ensemble modeling to evaluate potential futures of living marine resources. *Ecological Applications*, **23**(4), 742–754.

Gaylard, J.D. and Bergh, M.O. 2004. A species splitting mechanism for application to the commercial hake catch data 1978 to 2003. *Unpublished report, Marine and Coastal Management, South Africa WG/09/04/D:H:21.*

Giorgi, F. and Mearns, L. 2002. Calculation of average , uncertainty range , and reliability of regional climate changes from AOGCM simulations via the "Reliability Ensemble Averaging" (REA) method. *Journal of Climate*, **15**(10), 1141–1158.

Giorgi, F. and Mearns, L.O. 2003. Probability of regional climate change based on the Reliability Ensemble Averaging (REA) method. *Geophysical Research Letters*, **30**(12), 1–4.

Glazer, J.P. 2013. Updated CPUE and catch analyses for OMP 2014. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2013/SEP/SWG-DEM/49.*

Government Printer. 1977. *Section 3 of the Territorial Waters (Amendment) Act.* Government Printer, Pretoria, South Africa.

Government Printer. 1994. *Maritime Zones Act.* Government Printer, Pretoria, South Africa.

Haddon, M. 2001. Monte Carlo modelling. *Chap. 7, pages 175–196 of: Modelling and Quantitative Methods in Fisheries.* United States of America: Chapman and Hall/CRC.

Hauck, M. and Sowman, M. 2003. Introduction. *Chap. 1, page 2 of:* Hauck, M. and Sowman, M. (eds), *Waves of Change: Coastal and Fisheries Co-management in South Africa.* Cape Town: University of Cape Town Press.

Hawkins, E. and Sutton, R. 2009. The potential to narrow uncertainty in regional climate predictions. *American Meteorological Society*, **90**(8), 1095–1107.

Hilborn, R. and Walters, C.J. 1992. *Quantitative fisheries stock assessment: choice, dynamics and uncertainty.* Chapman and Hall, Inc. Great Britain, 1–550.

Hillary, R.M., Preece, A.L., Davies, C.R., Kurota, H., Sakai, O., Itoh, T., Parma, A.M., Butterworth, D.S., Ianelli, J. and Branch, T.A. 2015. A scientific alternative to moratoria for rebuilding depleted international tuna stocks. *Fish and Fisheries*, **17**(2), 469–482.

Hoeting, J., Adrian, D.M. and Volinsky, C.T. 1998. Bayesian model averaging. *Department of Statistics, University of Washington Technical Report 335*, 1–37.

Howe, J.P. (ed). 2017. *Making climate change history: primary sources from global warming's past.* University of Washington Press, 1–380. [Accessed via Google books].

Hutton, T. 2003. Industry-Government co-management arrangements in the South African offshore demersal hake fishery. *Chap. 9, pages 200–225 of:* Hauck, M. and Sowman, M. (eds), *Waves of Change: Coastal and Fisheries Co-management in South Africa.* University of Cape Town Press.

IBM Corp. 2016. *IBM SPSS Statistics for Windows, Version 24.0.*

IBM Knowledge Center. 2012. *Measures for Interval Data (Proximities command).*

ICSEAF. 1989. Historical series data selected for Cape hakes assessment. *ICSEAF document SAC/89/Doc/3.*

International Whaling Commission. 2015. Report of the Working Group on Ecosystem Modelling (EM) Annex K1. *J. Cetacean Res. Manage. 16 (Suppl.)*, 277–290.

Johnston, S.J. and Butterworth, D.S. 2005. Evolution of operational management procedures for the South African West Coast rock lobster (*Jasus lalandii*) fishery. *New Zealand Journal of Marine and Freshwater Research*, **39**(3), 687–702.

Johnston, S.J. and Butterworth, D.S. 2011. On specifications for OMP-2011 and associated trials. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/MAY/2011/SWG-WCRL/24*, 1–12.

Johnston, S.J. and Butterworth, D.S. 2017a. A summary of the west coast rock lobster fishery. *Unpublished report, MARAM document MARAM/IWS/2017/WCRL/BG1*, 1–8.

Johnston, S.J. and Butterworth, D.S. 2017b. Summary of key issues for discussion at the International Workshop regarding the estimation of the magnitude and trends of poaching of West Coast rock lobster. *Unpublished report, MARAM document MARAM/IWS/2017/WCRL/P2*, 1–10.

Johnston, S.J. and Butterworth, D.S. 2017c. The South Coast Rock Lobster Reference Case Operating Model. *Unpublished report, MARAM document MARAM/IWS/2017/SCRL/BG2*, 1–26.

Knutti, R. 2010. The end of model democracy? An editorial comment. *Climate Change*, **102**, 395–404.

Koers, A.W. 1973. *International regulation of marine fisheries. A study of regional fisheries organisations.* Tech. rept. London, 1–368. [Accessed via Google books].

Krishnamurti, T.N., Kishtawal, C.M., LaRow, T.E. and Bachiochi, D.R. 1999. Improved weather and seasonal climate forecasts from multimodel superensemble. *Science*, **285**(5433), 1548–1550.

Lallemand, P., Bergh, M., Hansen, M. and Purves, M. 2016. Estimating the economic benefits of MSC certification for the South African hake trawl fisher. *Fisheries Research*, **182**, 98–115.

MATLAB. 2016. The MathWorks Inc., Natick, Massachusetts, United States.

McKinlay, J.P. and de la Mare, W.K. 2015. Why BIC is not always (and may never be) an appropriate criterion for selecting terms in complex ecological models. *International Whaling Commission Technical Report SC/66a/EM/1*, 1–13.

McSweeney, C.F., Jones, R.G. and Booth, B.B.B. 2012. Selecting ensemble members to provide regional climate change information. *Journal of Climate*, **25**(20), 7100–7121.

Meehl, G.A., Covey, C., Delworth, T., Latif, M., McAvaney, B., Mitchell, J.F.B., Stouffer, R.J. and Taylor, K.E. 2007. The WCRP CMIP3 multimodel dataset: A new era in climate change research. *Bulletin of the American Meteorological Society*, **88**, 1383–1394.

Murphy, J.M., Sexton, D.M.H., Barnett, D.N., Jones, G.S., Webb, M.J., Collins, M. and Stainforth, D.A. 2004. Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, **430**(7001), 768–772.

New, M., Lopez, A., Dessai, S. and Wilby, R. 2007. Challenges in Using Probabilistic Climate Change Information for Impact Assessments : An example from the Water Sector Challenges in using probabilistic climate change information for impact assessments : an example from the water sector. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, **365**(1857), 2117–2131.

NOAA. 1993. *The historical development of fisheries science and management.* [Accessed from https://goo.gl/mabFZs and checked on 10/02/2018].

Oanta, G.A. 2018. International organizations and deep-sea fisheries: current status and future prospects. *Marine Policy*, **87**, 51–59.

OECD. 2009. *Strengthening Regional Fisheries Management Organisations.* Paris: OECD Publishing, 1–18.

Oreskes, N. and Finley, M.C. 2008. *A historical analysis of U.S. Fisheries Science, Development and Management, 1945-1995.* Tech. rept. University of California, San Diego, 1–3.

Parma, A., Davies, C., Hoyle, S. and Preece, A. 2017. Report of the Eighth Operating Model and Management Procedure Technical Meeting. *Commission for the Conservation of Southern Bluefin Tuna Technical Report, Seattle USA*, 1–32.

Payne, A.I.L. 1989. Cape hakes. *Pages 136–147 of:* Payne, A.I.L. and Crawford, R.J.M. (eds), *In Oceans of Life off Southern Africa.* Cape Town: Vlaeberg Publishers.

Payne, A.I.L. and Punt, A.E. 1992. Biology and fisheries of South African Cape hakes (*M.capensis* and *M. paradoxus*). *Pages 15–47 of:* Alheit, J. and Pitcher, T.J. (eds), *Hake: biology, fiheries, and markets.* Chapman and Hall.

Payne, A.I.L. and Punt, A.E. 1995. Biology and fisheries of South African hakes. *Pages 15–47 of:* Alheit, J. and Pitcher, T.J. (eds), *Hake: Fisheries, Ecology and Markets.* London: Chapman and Hall.

Punt, A.E. 1993. The comparative performance of production-model and ad hoc tuned VPA based feedback-control management procedures for the stock of Cape hake off the west coast of South Africa. *Canadian Special Publication of Fisheries and Aquatic Sciences*, 283–300.

Punt, A.E. 1994. Assessments of the stocks of Cape hakes (*Merluccius spp.*) off South Africa. *South African Journal of Marine Science*, **14**(1), 159–186.

R Core Team. 2015. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [https://www.R-project.org/].

Rademeyer, R.A. 2012. *The evolution of management procedures for the South African hake resource in the 2000s.* PhD thesis, University of Cape Town, 1–379.

Rademeyer, R.A. 2014a. Hake Candidate Management Procedures testing methodology. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/JULY/SWG-DEM/22*, 1–11.

Rademeyer, R.A. 2014b. Output from the South African Hake OMP-2014 for the 2015 TAC recommendation. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/OCT/SWG-DEM/58*, 1–4.

Rademeyer, R.A. and Butterworth, D.S. 2014a. Candidate Management Procedures projections for the South African hake resource. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/AUG/SWG-DEM/33*, 1–15.

Rademeyer, R.A. and Butterworth, D.S. 2014b. Final CMP projections for the South African hake resource. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/OCT/SWG-DEM/52*, 1–18.

Rademeyer, R.A. and Butterworth, D.S. 2014c. Results leading to a Proposal for a Reference Set of Operating Models for Testing the 2014 OMP Revision for the South African hake resource. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/MAR/SWG-DEM/14*, 1–14.

Rademeyer, R.A. and Butterworth, D.S. 2014d. Specifications of the South African Hake 2014 Reference Case Assessment. *Unpublished report, MARAM document MARAM/IWS/DEC14/Hake/P2*, 1–26.

Rademeyer, R.A., Butterworth, D.S. and Plagányi, É.E. 2008. Assessment of the South African hake resource taking its two-species nature into account. *African Journal of Marine Science*, **30**(2), 263–290.

Rademeyer, R.A., Fairweather, T., Glazer, J.P., Leslie, R.L. and Butterworth, D.S. 2010. The 2010 Operational Management Procedure for the South African *Merluccius paradoxus* and *M. capensis* resources. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2010/OCTOBER/SWG-DEM/59*, 1–36.

Rademeyer, R.A., Butterworth, D.S., Cooper, R., Durholtz, M.D., Fairweather, T.P., Glazer, J.P., Leslie, R.W., Singh, L. and Somhlaba, S. 2014. The 2014 Operational Management Procedure for the South African *Merluccius paradoxus* and *M. capensis* resources. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/OCT/SWG-DEM/64*, 1–28.

Redfern, J.V., Moore, T.J., Fiedler, P.C., de Vos, A., Brownell Jr, R.L., Forney, K.A., Becker, E.A. and Ballance, L.T. 2017. Predicting cetacean distributions in data-poor marine ecosystems. *Diversity and Distributions*, **23**(4), 394–408.

Ross-Gillespie, A. 2016. *Modelling cannibalism and inter-species predation for the Cape hake species Merluccius capensis and M. paradoxus*. PhD thesis, University of Cape Town, 1–195.

SADSTIA. 2016. *SADSTIA: South African Deep-Sea Trawling Industry Association*. [http://www.sadstia.co.za/].

Sanderson, Benjamin M., Knutti, Reto and Caldwell, Peter. 2015a. A representative democracy to reduce interdependency in a multimodel ensemble. *Journal of Climate*, **28**(13), 5171–5194.

Sanderson, Benjamin M., Knutti, Reto and Caldwell, Peter. 2015b. Addressing interdependency in a multimodel ensemble by interpolation of model properties. *Journal of Climate*, **28**(13), 5150–5170.

Schwarz, G. 1978. Estimating the dimension of a model. *Annals of Statistics*, **6**(2), 461–464.

Scott, F., Jardim, E., Millar, C.P. and Cerviño, S. 2016. An applied framework for incorporating multiple sources of uncertainty in fisheries stock assessments. *PLoS ONE*, **11**(5), 1–21.

Smith, F.E. 1966. *The Politics of conservation*. Pantheon Books, 1–338. [Accessed via Google books].

Somhlaba, S. and Leslie, R.W. 2014. Catch-at-length information and proportions of females for Merluccius paradoxus and M. capensis off the South African coast from 2000 to 2010. *Unpublished report, Department of Agriculture, Forestry and Fisheries, South Africa FISHERIES/2014/AUG/SWG-DEM/38*.

Spence, M.A., Blanchard, J.L., Rossberg, A.G., Heath, M.R., Heymans, J.J., Mackinson, S., Serpetti, N., Speirs, D., Thorpe, R.B. and Blackwell, P.G. 2017. Multi-model ensembles for ecosystem prediction. *Cornell University Library, arXiv:1709.05189*, 1–41.

Starr, P.J. and Webber, D.N. 2016. The 2015 stock assessment of red rock lobsters (*Jasus edwardsii*) in CRA 5 and development of management procedures. *New Zealand Fisheries Assessment Technical Report 2016/41*, 1–119.

Taylor, K.E., Stouffer, R.J. and Meehl, G.A. 2012. An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, **93**(4), 485–498.

Tebaldi, C. and Knutti, R. 2007. The use of the multi-model ensemble in probabilistic climate projections. *Phil. Trans. R. Soc.*, **365**(1857), 2053–2075.

Tetzlaff, K. 2015. The role of regional organisations. *Chap. 8, page 106 of:* Warner, R. and Kaye, S. (eds), *Routledge Handbook of Maritime Regulation and Enforcement*, 1st edn. London: Routledge. [Accessed via Google books].

Vrancken, P.H.G. 2011. Exploitation of marine resources. *Chap. 11, pages 258–309 of: South Africa and the Law of the Sea*. Martinus Nijhoff Publishers.

Webster, M.D., Babiker, M., Mayer, M., Reilly, J.M., Harnisch, J., Hyman, R., Sarofim, M.C. and Wang, C. 2002. Uncertainty in emissions projections for climate models. *Atmospheric Environment*, **36**(22), 3659–3670.

Went, A.E.J. 1972. Seventy years agrowing: a history of the International Council for the Exploration of the Sea, 1902-1972. *RPV*, **165**, 10–22. [Accessed via Google books].